TAHOE FOREST
HOSPITAL DISTRICT

2026-09-08 OPEN SESSION Board Quality Committee Meeting

Tuesday, September 08, 2026 at 1:00 p.m.

Aspen Conference Room - Tahoe Forest Hospital

10800 Donner Pass Rd, suite 200, Truckee CA 96161

Meeting Book - 2026-09-08 OPEN SESSION Board Quality Committee Meeting

TAHOE FOREST
HOSPITAL DISTRICT

BOARD QUALITY COMMITTEE
AGENDA

TO BE HELD ON

TUESDAY, SEPTEMBER 8, 2026, AT 1:00 PM

TAHOE FOREST HOSPITAL – ASPEN CONFERENCE ROOM

10800 DONNER PASS RD, SUITE 200, TRUCKEE, CA 96161

1. **CALL TO ORDER**
2. **ROLL CALL**
3. **DELETIONS/CORRECTIONS TO THE POSTED AGENDA**
4. **INPUT – AUDIENCE**

   This is an opportunity for members of the public to address the Committee on items which are not on the agenda. Please state your name for the record. Comments are limited to three minutes. Written comments should be submitted to the Board Clerk 24 hours prior to the meeting to allow for distribution. Under Government Code Section 54954.2 – Brown Act, the Committee cannot take action on any item not on the agenda. The Committee may choose to acknowledge the comment or, where appropriate, briefly answer a question, refer the matter to staff, or set the item for discussion at a future meeting.
5. **APPROVAL OF MINUTES**◈

   5.1. 05/27/2026 Open Session Board Quality Committee .... ATTACHMENT
6. **CLOSED SESSION**

   6.1. Hearing (Health & Safety Code § 32155)

   Subject Matter: Case Review

   Number of items: One (1)

   6.2. Approval of Closed Session Minutes◈

   6.2.1. 05/27/2026 Closed Session Board Quality Committee
7. **OPEN SESSION – CALL TO ORDER**
8. **REPORT OF ACTIONS TAKEN IN CLOSED SESSION**
9. **INFORMATIONAL REPORTS**

   9.1. Patient & Family Centered Care

   9.1.1. Patient & Family Advisory Council (PFAC) Update .... ATTACHMENT

   Quality Committee will receive a brief verbal update on the initial calendar year activities of the Patient and Family Advisory Council (PFAC).

   9.2. Patient Safety

   9.2.1. BETA HEART Progress Report .... ATTACHMENT*

   Quality Committee will receive a progress report regarding the BETA Healthcare Group Culture of Patient Safety program.

◈ Denotes Action Item

10. ITEMS FOR COMMITTEE DISCUSSION AND/OR RECOMMENDATION◈

10.1. Safety First .... ATTACHMENT

The Board Quality Committee will review the Emergency Codes and alerts reminder.

10.2. Policy Review◈

10.2.1. AGOV 1901 Service Animals & Pet Assisted Therapy .... ATTACHMENT

10.2.2. AGOV 1602 Peer Support (Care for the Caregiver) .... ATTACHMENT

10.3. Board Quality Committee Charter .... ATTACHMENT

The Board Quality Committee Charter will be referenced as needed during the meeting.

10.4. Clinical Governance Committee Report .... ATTACHMENT

The Committee will receive a progress report regarding the clinical governance committee, including artificial intelligence utilization and future plans.

10.5. Quality / Patient Safety / Roundtable

The Committee will conduct roundtable discussion on insights, identification of emerging challenges, and strategic opportunities to enhance care delivery and organizational safety culture.

10.6. Board Quality Education .... ATTACHMENT

The Committee will review the educational article listed below and discuss topics for future board quality education.

Artificial Intelligence in Health Care article

11. REVIEW FOLLOW UP ITEMS / BOARD MEETING RECOMMENDATIONS

12. NEXT MEETING DATE

13. ADJOURN

AMR:smj

*Denotes material (or a portion thereof) may be distributed later.

Note: It is the policy of Tahoe Forest Hospital District to not discriminate in admissions, provisions of services, hiring, training and employment practices on the basis of color, national origin, sex, religion, age or disability including AIDS and related conditions. Equal Opportunity Employer. The telephonic meeting location is accessible to people with disabilities. Every reasonable effort will be made to accommodate participation of the disabled in all of the District's public meetings. If particular accommodations for the disabled are needed or a reasonable modification of the teleconference procedures are necessary (i.e., disability-related aids or other services), please contact the Clerk of the Board at (530) 582-3583 at least 24 hours in advance of the meeting.

◈ Denotes Action Item

QUALITY COMMITTEE
DRAFT MINUTES

Wednesday, May 27, 2026, at 3:00 p.m.
Aspen Conference Room – Tahoe Forest Hospital
10800 Donner Pass Rd, Suite 200, Truckee, CA 96161

1. CALL TO ORDER
Meeting was called to order at 3:02 p.m.

2. ROLL CALL
Board: Alyce Wong, Chair; Robert Darzynkiewicz, Board Member

Staff in attendance: Anna Roth, President & CEO; Dr. Brian Evans, Chief Medical Officer (zoom); Janet Van Gelder, Executive Director of Quality & Regulation & Oncology; Erin Madewell, Director of Quality & Regulations (zoom); Christine O'Farrell, Risk Manager; Dorothy Piper, Director of Medical Staff Services (zoom); Crystal Felix, CFO (zoom); Sarah Jackson, Clerk of the Board;

Other: none

3. CLEAR THE AGENDA/ITEMS NOT ON THE POSTED AGENDA
No changes were made to the agenda.

4. INPUT – AUDIENCE
None

5. APPROVAL OF MINUTES OF: 02/11/2026
Director Darzynkiewicz moved to approve the Open Session Board Quality Committee Minutes of February 11, 2026.

Open Session recessed at 3:05 p.m.

6. CLOSED SESSION
6.1. Hearing (Health & Safety Code § 32155)
Subject Matter: Case Review
Number of items: One (1)
Discussion was held on a privileged item.

6.2. Approval of CLOSED Session Minutes
6.2.1. 02/11/2026 Closed Session Board Quality Committee
Discussion was held on a privileged item.

7. OPEN SESSION
Open Session reconvened at 3:24 p.m.

8. REPORT OF ACTIONS TAKEN IN CLOSED SESSION

No reportable actions for 6.1. Item 6.2, Closed Session Minutes of February 11, 2026, were recommended for approval.

9. INFORMATIONAL REPORTS

9.1. Patient & Family Centered Care

9.1.1. Patient & Family Advisory Council (PFAC) Update

Quality Committee reviewed the attached update related to the activities of the Patient and Family Advisory Council (PFAC).

Executive Director reported on the most recent PFAC meeting including new members. Discussion was Held

9.1.2. BETA HEART Progress Report

Committee Reviewed the BETA HEART progress report for 2026. We will receive credit to our BETA invoice due to our efforts in these areas.

10. ITEMS FOR COMMITTEE DISCUSSION AND/OR RECOMMENDATION

10.1. Safety First

Janet Van Gelder, Executive Director of Quality, Regulations & Oncology reviewed the top 10 patient safety concerns of 2026.

The top 10 patient safety concerns for 2026 were reviewed. List has been distributed among department to raise awareness.

Significant discussion was held on item #1, "Navigating the AI Diagnostic Dilemma."

CEO recommends that CMO bring updates and reviews from the Clinical IT Governance Committee (CIC) to the Board Quality Committee on a periodic basis.

No Action was taken.

10.2. Board Quality Committee Charter

The Committee will reference the Charter as needed during the meeting.

Future adjustments to the Charter were discussed.

No Action was taken.

10.3. Process Improvement Report

10.3.1. Incidental Findings Process Improvement

The Committee reviewed the Incidental Findings Process Improvement Report. Noted was that we are missing follow through on incidental findings.

The Process Improvement, data gathering and ideal state was identified. Inconsistent workflows were found between departments, there were unclear handoffs, and there were differences in inpatients and outpatients when clinically relevant incidental findings were identified. Ideal state mapping occurred.

10.3.2. Interpreter Services Employee Education / Certification

The Committee reviewed interpreter services, employee education and certification.

The Top 10 languages utilized by the Language Line was reviewed by both audio and video. It is still recommended that we continue to utilize the Language Line for medical use for 24 x 7 coverage.

10.4. Board Quality Dashboard

The Committee reviewed the Board Quality Dashboard and provided input on the quality metrics. Suggested edits to the dashboard were reviewed.

Discussion was held.

No Action was taken.

10.5. Quality / Patient Safety / Risk Roundtable

The Committee conducted roundtable discussion. Director Darzynkiewicz enquired the TFHS Athletic Trainers: cost to our budget, are there quality measures, is something appropriate for the Health System to fund.

Extensive Discussion was held.

10.6. Board Quality Education

The Committee will review the educational article listed below and discuss topics for future board quality education.

Emergency Care Research Institute (ECRI). Top 10 Patient Safety Concerns 2026.

#9 - Emergency Department Boarding Contributes to Worse Patient Outcomes was reviewed. Discussion was held.

11. REVIEW FOLLOW UP ITEMS / BOARD MEETING RECOMMENDATIONS

Discussion was held.

12. NEXT MEETING DATE

The next committee date and time will be confirmed for August xx, 2026 at ___ pm.

13. ADJOURN

Meeting adjourned at 4:31 p.m.

Patient and Family Advisory Council (PFAC) Summary Report

May 2026-Aug 2026

Erin Madewell, MSN, RN – Director of Quality & Regulations

Summary of Monthly Topics

May 2026 – Dr. Ulland presented an update on primary care operations, including staffing capacity, appointment access challenges, and increasing provider workload. Discussion focused on long wait times for appointments, the growing burden of inbox management, and opportunities to improve message prioritization and response expectations. Members also explored technology limitations, the role of telehealth, and potential support resources to reduce administrative workload. Additional feedback centered on concerns regarding possible billing for MyChart communications and the need to maintain equitable access to care for all patients.

June 2026 – PFAC members participated in a review of a high-risk twin delivery case presented by Risk Management and Patient Safety, focusing on the balance between honoring patient preferences and ensuring safe, evidence-based care. The discussion explored opportunities to strengthen communication of risks and benefits, improve the event analysis process, and incorporate patient and family perspectives more consistently into investigations. Members recommended exploring additional communication approaches, including peer-to-peer messaging, and supported expanding family involvement in event reviews beyond current practices. The council also discussed completion of a PFAC self-assessment to evaluate the effectiveness of the group and support continued alignment with TFHD's strategic goals.

July 2026 – Kim McCarl presented on brand architecture. PFAC members provided feedback on two proposed brand architecture concepts, "Care Within Reach" and "Care for Every Adventure," evaluating how each aligns with TFHD's strategic plan and connection to the community. Discussion highlighted the strengths and potential limitations of both approaches, including concerns about overpromising access and ensuring the brand resonates with patients facing serious illness. Members emphasized the importance of branding that reflects partnership, shared decision-making, and patient empowerment. The meeting also included follow-up discussion on incorporating patient and family perspectives into safety event investigations and improvement efforts.

Aug 2026 – PFAC members participated in a discussion on healthcare quality presented by the Quality Department. This included the domains of quality, CMS Star Ratings, and publicly reported performance measures, with a focus on identifying which metrics are most meaningful to patients and the community. The council emphasized that patient preferences are a critical component of the quality experience and noted that definitions of quality may vary based on individual patient goals, values, and circumstances. Members provided feedback on areas of care that may not be adequately reflected in traditional quality measures and discussed preferred methods for sharing quality information with the public. The meeting reinforced the importance of incorporating the patient perspective when evaluating and communicating healthcare quality.

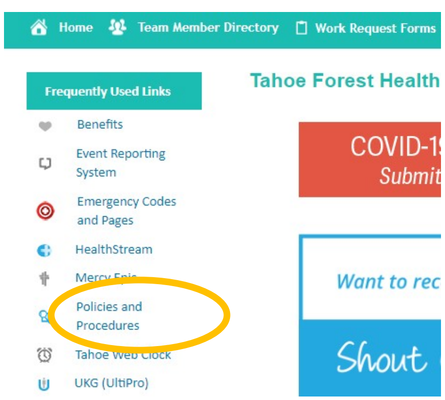
Safety First

tip of the week

Know Your Codes & Overhead Pages

Tahoe Forest Hospital District has an Emergency Code system to rapidly notify key personnel and staff of various emergencies.

You can find the list on the TFHD intranet home page:



ALL CODES: In the Hospitals: Call x222 to immediately reach a hospital operator TFH Outbuildings: Call 9-1-1 to reach emergency personnel	
Code Red	Fire
Fire Response Plan	*Using a Fire Extinguisher*
R = Rescue	P = Pull
A = Alarm	A= Aim
C = Contain	S = Squeeze
E = Extinguish	S = Sweep (the base of the fire)
Code Blue/Code White	Medical Emergency/Pediatric Medical Emergency
Code Yellow	Bomb Threat
Code Gray	Combative Person(s)
Code Silver	Person(s) with Weapons/Hostages
Code Pink/Code Purple	Infant Abduction/Child Abduction
Code Orange	Hazardous Material
Code Crimson	Massive Blood Transfusion
Code Tan	Facility Lockdown
Code Trauma	Trauma Case in Emergency Department
Code Triage Internal/External	Disaster Inside or Outside the Hospital
Code 250	Patient or Visitor Medical Emergency on Hospital Grounds/Cancer Center
Rapid Response	Patient in Distress
Stroke Alert	Patient with Stroke Symptoms

Refer to your department emergency plan.
Complete and send your Disaster Resource List to the Labor Pool when appropriate.
In the event of a disaster, report to your department.

Questions? **Call the Quality Department** Janet Van Gelder x6629, Erin Madewell x6328, Christine O'Farrell x6637, Alix Bezaire x6423, Tena Mather x6334, Svieta Schopp x8231, Barb Widder x3541

Status Pending PolicyStat ID 21410012

Origination Date	05/2019	Department	Governance - AGOV
Last Approved	N/A		
Effective	Upon Approval		
Last Revised	09/2026		
Next Review	3 years after approval		

Service Animals & Pet Assisted Therapy, AGOV-1901

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RISK:

If a standardized process for Service Animals, Pet Assisted Therapy (PAT) Animals, and pet visitation is not followed this could result in noncompliance with the Americans with Disabilities Act (ADA), and patient harm due to not abiding by nationally-recognized safety and infection prevention guidelines.

POLICY:

A. Persons with disabilities are entitled to ~~bring their~~be accompanied by a service animal, as defined by the Americans with Disability Act (ADA), onto Tahoe Forest Hospital District (TFHD) and Incline Village Community Hospital (IVCH) campuses and receive reasonable accommodation. Service animal is defined by the Americans with Disabilities (ADA) as a dog (or in limited cases, a miniature horse) that is individually trained to do work or perform tasks for the benefit of an individual with a disability. Animals whose sole function is to prove comfort or emotional support do not qualify as service animals under the ADA. Service animals are not required to be certified~~ service animals (nonhuman primates and reptiles excluded) onto the Tahoe Forest Hospital District (TFHD) and Incline Village Community Hospital (IVCH) campuses and receive reasonable accommodation. Service animal is a legal term defined by the Americans with Disabilities (ADA) as any animal that assists a person with one or more daily activities.~~, registered, or licensed as a condition of access.

B. Pet-assisted therapy (PAT) animals are allowed for the benefit of patients. PAT sessions consist of one dog handler (Truckee-Tahoe Humane Society (TTHS) trained volunteer animal handler) and one approved dog spending time with one patient at a time who agrees to PAT and is a candidate for PAT on the day of the visit.

Personal pets and Emotional Support Animals are NOT permitted in the hospital or other health system locations unless designated as service animals or therapy animals, or unless prior approval has been obtained by the Risk Manager or respective Director/Manager/Supervisor

Definitions:

A. **Service Animal** – A dog, or in limited cases a miniature horse, that is specifically trained to do work or perform tasks for the benefit of a person with a disability(s). If an animal meets this definition, it is considered a Service Animal under the Americans with Disabilities Act, regardless of whether it has been licensed or certified. ~~This category~~Service Animals in training are not recognized under the ADA; however, they may ~~include~~be permitted in accordance with applicable state law and facility policy. A Service ~~Animals in training. A Service~~ Animal is not considered a pet.

B. **Disability** – The consequence of an impairment that may be physical, cognitive, mental, sensory, emotional, developmental, or some combination of these.

C. **Emotional Support Animal** – An animal, usually a personal pet, that provides therapeutic benefits to its owner through companionship and affection. Emotional Support animals are not specifically trained to perform tasks for a person who suffers from emotional disabilities. Emotional Therapy animals are not considered service animals and are not included in the Americans with Disabilities Act.

D. **Pet-Assisted Therapy (PAT) Animal** – An animal, usually a personal pet, that with their owner, has successfully completed training and maintains certification as a Therapy Animal by an approved, accreditation organization. PAT animals are not considered service animals and are not included in the Americans with Disabilities Act.

E. **Pet** – a domestic animal kept for pleasure or companionship, and/or an animal not recognized as a PAT Dog or Service Animal.

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PROCEDURE:

A. **Service Animals**

1. Under the ADA, an employee may ask two distinct questions to determine if the animal in question is a Service Animal:
    a. Is the animal required because of a disability?
    b. What work or task is the animal trained to perform?
2. IMPORTANT: Under the ADA, staff may not request any documentation for the dog, may not inquire about the nature of the person's disability, or require proof that the dog is trained.
3. Individuals with a Service Animal must be allowed to go anywhere in the facility that patients and the general public are allowed to go, unless a legitimate safety requirement or infection control risk cannot be mitigated. An employee with a service animal must be granted the same access as an employee in the same job title without a service animal.
4. A Service Animal is not required to wear a harness, tags, or other information indicating that it is a Service Animal. Staff may not require proof of certification or

other such evidence of Service Animal status before permitting the Service Animal to accompany the person with a disability.

5. Persons who use Service Animals are entitled to be accompanied by their Service Animals during the course of visits to this facility regardless of whether the animals are working or performing services at all times, and regardless of whether health care staff could perform essentially the same services provided by the Service Animal.
6. In addition to ensuring the independence of the person with a disability, keeping an animal and handler together helps to maintain the animal's training and the bond.
7. Tahoe Forest Hospital District (TFHD) will permit a person with a disability to be accompanied by his/her Service Animal in all areas of the facility in which that person would otherwise be allowed unless a legitimate safety requirement or infection control risk cannot be mitigated.
    a. Areas from which Service Animals may be excluded would include those areas not accessible to the general public. This could include any area where visitors need to take protective infection control measures, e.g., using gloves, wearing gowns, and masks, wearing protective equipment, paying strict attention to hand hygiene and being free of dermatologic conditions, and no similar infection control measures could be reasonably imposed on a Service Animal.
    b. Service Animals may generally be excluded from the following restricted access specialty care units:
        i. Operating rooms
        ii. Labor and Delivery
        iii. Intensive Care Unit
        iv. Those areas in which transmission based precautions are in place, e.g., rooms or units that require special ventilation for high-risk immunocompromised patients, patients with open sores or exposed areas of skin, neutropenia (neutrophils less than 1000), all airborne infection isolation rooms and for all patients with airborne infections.
    c. Justification for restriction must be documented when exclusion occurs, including infection control rationale.
8. Procedures for Decisions Regarding Service Animals:
    a. Risk Management, in conjunction with Infection Control, is responsible for designating all restricted access areas of the facility and will review this on a regular basis. Risk Management and/or Human Resources may make individual decisions regarding Service Animals in accordance with this policy, the relevant provisions of the ADA, and any other relevant law.
    b. Other than the "Restricted Access Areas" listed above, Service animals should not be automatically excluded from any area of the facility, unless the appropriate analysis and determination has been made. For example, if certain immunocompromised patients are able to receive visitors who

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are not required to adhere to any special infection control measures, it likely will be appropriate for a staff member, employee, volunteer, patient or visitor who uses a Service Animal to enter that care area.

c. In the event that a question or dispute arises about whether a Service animal can accompany its owner in a particular area of this facility, Risk Management and/or Human Resources, in conjunction with Infection Control, must make that decision on a case-by case basis and take into account:

    i. The particular Service Animal

    ii. The needs of the affected person(s) and patient(s)

    iii. The health care situation

9. Consultation with Persons Who Use Service Animals:

    a. If a person who uses a Service Animal is expected to be admitted as a patient to this facility, admitting staff should determine what arrangements the patient wants to make regarding his/her Service Animal, including the patient's preference to be accompanied by the animal.

    b. All patients and visitors who use Service Animals must be advised that the care or supervision of a Service Animal is solely their responsibility and that facility personnel may not provide care, food, or a special location for the animal.

    c. The patient may designate a family member or other volunteer to care for the Service Animal.

    d. In the event that a patient decides to leave the Service Animal at home, a family member or volunteer may bring the animal in for visits with the patient to help maintain the bond between the person and the Service Animal.

    e. In those instances where it is not possible to discuss arrangements for a Service Animal prior to regular admission or emergency room treatment, every effort should be made to discuss the patient's preferences regarding his/her Service Animal at the earliest possible time.

    f. Facility staff will advise the owner of a Service Animal where the animal can be taken to toilet and to exercise on the grounds of the facility. Service Animals are to be accompanied by the owner or the owner's designated responsible party at all times. TFHD and/or IVCH staff are not responsible for the care, feeding, exercising, or toileting of animals.

    g. The handler is responsible for the control of the Service Animal at all times (leash, harness, or tether unless contraindicated by disability). The handler shall ensure the Service Animal is housebroken and in good health and will prevent the Service Animal from coming in contact with invasive devices, wounds, sterile equipment, or food.

    h. The ~~patient or his/her designee~~handler is responsible for the care and control of the service animal. TFHD and/or IVCH reserves the right to have a service animal removed from the premises if it poses a threat to

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patients, visitors, or staff. The Service Animal may be removed if it is out of control and the handler does not take corrective action, it is not housebroken, or it poses a direct threat that cannot be mitigated.

10. Separation of the Owner and the Service Animal:
    a. If, in accordance with this policy, it becomes necessary to separate the Service Animal from its owner, health care personnel will make all reasonable efforts to help facilitate the transfer of the animal to a designated person prior to the separation.
    b. At THFD locations, in the event that a Service Animal must be separated from the handler, and no designee is presently available, health care personnel will contact the Humane Society of Truckee-Tahoe (HSTT) at 530-582-2472, to make temporary arrangements for the care and supervision of the animal.
    c. At IVCH locations, in the event that a Service Animal must be separated from the handler, and no designee is presently available, health care personnel will contact the Washoe County Sheriff's Office (WCSO) either by dialing 911, or calling WCSO Dispatch at 775-322-3647, option 1. WCSO is available 24 / 7 and work collaboratively with Washoe County Regional Animal Services which can accommodate a "safe hold."
    d. Efforts should be made to explain the particular rationale for the separation to the owner and to help the owner make alternative arrangements for the care of the animal.
11. Other Guidance:
    a. In the event someone has severe allergies to animals, or has asthma, facility staff will make a risk assessment in accordance with the criteria in the policy.
    b. Staff is expected to take reasonable steps to ensure that any potential harm is minimized by moving affected staff, patients, or visitors to other areas or rooms or making other reasonable modifications.
    c. Care must be taken to ensure that any relocation of patients are made without regard to disability, and that persons using Service Animals are not the individuals routinely asked to relocate.
    d. If any patient must be relocated to accommodate his/her or someone else's need to be accompanied by a Service Animal, neither person may be charged a higher rate than they would have been charged in their original location.
    e. A Service Animal is permitted to accompany its owner to any area(s) where health care staff, visitors, and patients are permitted to enter without taking heightened infection control precautions.
12. Complaints Regarding Service Animals: Persons with disabilities who use Service Animals and any other individuals may file a complaint with the facility setting forth the nature of the complaint and the pertinent details and what action they wish taken. Persons who wish to file a complaint should follow procedures set forth in the

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"Patient/Family Grievance" policy. Persons with complaints may also file the complaints with federal or state agencies, if they wish.

B. **Pet Assisted Therapy (PAT) Animals – General Provisions:**

1. Typically, a PAT session consists of one dog handler (Humane Society trained volunteer animal handler) and one certified dog spending time with one patient/ resident at a time who agrees to PAT, and is a candidate for PAT on the day of the visit.
    a. The physician will notify the nursing station if PAT is not authorized or rely on the determination of the patient/resident nurse on appropriateness of PAT based on patient/resident ability for appropriate interaction with dog.
    b. Dog handler agrees to abide by this policy and the Humane Society of Truckee-Tahoe's Pet Assisted Therapy program guidelines.
    c. In selected locations (e.g. outpatient clinics or Long Term Care/Extended Care Center (ECC)), the presence of a PAT dog may result in interaction with more than one patient/resident and those accompanying patients/ residents in the common areas. Before entering the common area(s), volunteer dog handler must check with staff of the clinic or ECC if patients/residents and those accompanying them are agreeable to the PAT visit.
2. Volunteers (animal handlers) of the Humane Society of Truckee-Tahoe may visit inpatients, outpatients, or residents for the purpose of PAT sessions after checking with approved nursing station, outpatient reception, or Cancer Center main desk, and infusion area nursing station.
    a. For inpatients, the designated entrances are: first floor main entrance, 2nd floor South entrance, or the entrance to Long-term Care.
    b. Sign in is required at approved PAT nursing units and other locations.
    c. PAT Volunteers are instructed to visit the Cancer Center first when multiple PAT visits are planned for the same day.
    d. PAT visits are on a voluntary basis and not during animal handlers work hours.
    e. PAT volunteer animal handlers must sign the PAT Handler Volunteer Waiver of Liability before providing volunteer services at any TFHD site location.
3. The dog must be appropriately identified as a therapy dog by wearing a TFHD ID badge and a clean therapy dog vest. The dog must be:
    a. Certified by the AKC Canine Good Citizen Test (includes temperament evaluation);
    b. At least one year of age;
    c. Spayed or neutered.
4. Dogs must have current rabies vaccination, be free of ectoparasites (e.g. fleas, ticks) and have no sutures, open wounds, or obvious dermatologic lesions that could be

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associated with bacterial, fungal, viral or parasitic infestations.

a. Special testing may be indicated if the dog is epidemiologically linked to an outbreak of an infectious disease.

5. Pet Therapy dogs, and their approved handler, are welcome to visit patients who desire PAT, are able to interact with PAT dog appropriately, and have no open uncovered wounds in the following locations after checking in with nursing station first:
    a. Long-term Care: common areas, patio, or individual resident's rooms;
    b. Multi-Specialty Clinics (MSC), except procedure rooms.
    c. Home setting for Hospice and Home Health patients.
        i. Patients and/or family will request Pet-assisted Therapy visit.
        ii. Prior to the Pet-assisted therapy visit, the staff member/ volunteer will provide information about pet
        iii. therapy to the patient/family/caregiver.
        iv. A visit by pet therapy will be arranged upon approval by the patient/family.
        v. Pet therapy will be incorporated into the plan of care (POC).
        vi. Provision of pet therapy will be documented in the patient's electronic medical record (EMR)
        vii. The name of the animal involved and patient's response will be documented on the visit record (Nursing, HHA, MSW, Volunteer, etc) and will be entered/scanned into the EMR.
        viii. Staff/volunteers will remain with the pet throughout the entire visit along with the handle
6. Pet Therapy dogs, and their approved handler, are welcome for Peer Support during a group debrief after a critical incident, or for one on one Peer Support. This will be performed only in non-patient care areas such as conference rooms that are not accessed through a patient care area (i.e., Eskridge, Solarium), or located in non-clinical areas (i.e., Donner, Gateway), and outside locations on campus (weather permitting).
7. A pet therapy dog visit is defined as a short length of time (e.g. usually a few minutes to an hour), with a patient that has requested the interaction, for the purpose of providing affection and comfort.
8. Pet Therapy dogs are not allowed in:
    a. Surgical Services, including Operating Rooms, Procedure Rooms, Sterile Processing Department, Ambulatory Surgery, Post-Anesthesia Recovery Unit (PACU)
    b. Radiology Special Procedures Room
    c. Emergency Department
    d. Medical-Surgical Department

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e. Intensive Care Unit (ICU)
f. Women & Family Center
g. Laboratory or lab draw areas
h. Cancer Center
i. Food service e.g. cafe, food preparation, or food storage areas
j. Medication storage or preparation areas

9. All PAT volunteers will attend an orientation session by the PAT Coordinators at TFHD prior to beginning Pet Therapy and a PAT Coordinator will accompany volunteers and their dogs on their first visit to the health system.
10. TFHD reserves the right to have a PAT animal removed from the premises if it poses a threat to patients, visitors, or staff.

C. **Pets – General Provisions:**

1. Pets, as defined above, are generally NOT permitted in the facility. Generally only patients who have a life-threatening or terminal illness, and have requested a visit with their personal pet, are allowed pet visits.
2. Exceptions to this pet policy are on a case-by-case basis. Risk Management and Human Resources, as well as the patient and family, will be involved in making pet visitation decisions.
3. Animals participating in pet visitation sessions should be current and complete with regard to recommended immunizations and should be in good health.
4. Pet visits must be supervised by a handler who knows the animal and their behavior, and the area must be cleaned after visits according to standard cleaning procedures.
5. TFHD reserves the right to restrict pets on any TFHD property.

D. **Documentation requirements for all animals in the health care facility**: If requested, the handler/partner of a service/therapy animal or pet must show proof that the animal has met the following regulations:

1. Licensing: As appropriate, the animal must meet the licensing requirement of Nevada County, CA and wear the tags designated by the city. (For nonresidents, home city or state tags will be accepted in lieu of Nevada County, CA tags.)
2. Health Records: As appropriate, the animal must have a health statement, including vaccinations from a licensed veterinarian, dated within the past year. Preventative measures must be taken for flea and odor control. Animals should be routinely screened for enteric parasites and should have no obvious dermatologic lesions that could be associated with bacterial, fungal, or viral infections. Animals should be clean and well groomed.
3. Animals that are ill or in poor health must not be taken into public areas.

E. **General provisions applicable to all animals:**

1. Infection Prevention and Control:

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a. The most important infection control measure to prevent potential disease transmission is strict enforcement of hand washing or hand hygiene measures (using alcohol-based agents when a sink is not available) for all patients, staff, and residents after handling the animals.

b. Staff is expected to follow standard infection control and environmental surface cleaning procedures following visitation by a Service or PAT Animal.

c. Care should also be taken to avoid direct contact with animal's urine and feces. Clean-up of these substances from environmental surfaces requires gloves and the use of leak-resistant (e.g., "zip-lockable") plastic bags to discard absorbent material used in the process of the clean-up (similar to the disposal of diapers).

d. The area of the spill should be cleaned with a facility-approved disinfectant.

e. Relief areas include the nearest grassy areas outdoors, such as the spaces outside the external doors.

2. Behavior/etiquette of handlers and animals in the health care facility:

   a. The handler will provide the animal with an opportunity to relief itself outside before entry to the PAT visit area.

   b. The animal must be under partner/handler control at all times with a non-retractable leash that is 4-6 feet or less in length.

   c. The animals will not be allowed to wear choke collar or chain, only clean standard cloth or leather collar will be allowed.

   d. The animal may be asked to leave the premises if it exhibits aggressive or threatening behaviors or in any way poses a risk to patients, residents, staff, or visitors.

   e. The animal must not display any disruptive behaviors such as barking, whining, growling, or pawing.

   f. The animal must not sniff people, food, or the belongings of others.

   g. The animal must not initiate contact with others without the partner/handler's permission.

   h. The animal must not block an aisle or passageway.

   i. No food will be provided/available for the animal at the visit location.

   j. No animal bedding or toys will be allowed at the visit location.

3. Grooming requirements:

   a. The animal's coat will be brushed or combed before a visit to remove loose hair, dander, and other debris.

   b. The animal's nails will be kept short and free of sharp edges.

F. **Education and Training of Staff Regarding the Policy**: TFHD will conduct periodic training on the issue of animals in the healthcare facility and ensure that employees are advised about the

COPY

policy and the procedures for handling questions about animals in this health care facility.

G. **Reasonable Modification of Policies, Practices, and Procedures:** On occasion, there may be situations not addressed in this policy where this facility will need to make certain changes to accommodate a person with a disability who uses a Service Animal or a patient requesting a pet visit. This facility will make reasonable modifications to its policies, practices, and procedures to ensure that persons with disabilities enjoy the full protection of the ADA.

H. **Responsibility:** All TFHD employees, and contractors, are responsible for enforcing, following, and abiding by this policy and procedure.

Related Policies/Forms:

PAT Handler Volunteer Waiver of Liability

References:

CDC reference: Guidelines for Environmental Infection Control in Health-Care Facilities (2003), last updated July 2019

~~Additional Resource Information: Regulations pertaining to Title III of the Americans with Disabilities Act prohibiting discrimination on the basis of disability by public accommodations and commercial facilities, 28 C.F.R.§36.101 et seq. See in Particular: the ADA 2010 revised requirements for service animals. https://www.ada.gov/service_animals_2010.htm~~

U.S. Department of Justice, Civil Rights Division. (2020, February 28). *ADA requirements: Service animals*. https://www.ada.gov/resources/service-animals-2010-requirements/

COPY

All Revision Dates

09/2026, 02/2025, 09/2024, 04/2024, 06/2022, 04/2022, 12/2021, 06/2021, 06/2019, 06/2019, 05/2019

Attachments

PAT Liability Waiver Form.pdf

Approval Signatures

Step Description	Approver	Date
	Devon Kim: Executive Assistant	Pending

PAT Handler Volunteer Waiver of Liability

By indicating your acceptance, you understand, agree, warrant and covenant as follows:

As a volunteer handler of a pet assisted therapy (“PAT”) animal at Tahoe Forest Health System (the “Site”), I hereby represent and acknowledge that I am solely liable for all claims, liabilities, damages and debts of any type whatsoever that may arise on account of my activities and those of my pet assisted therapy animal while on Site. Additionally, (1) I HEREBY RELEASE AND SHALL DEFEND, INDEMNIFY AND HOLD HARMLESS, Tahoe Forest Health System and its officers, directors, shareholders, partners, employees, members and agents (the "Releasee"); FROM EVERY CLAIM AND ANY LIABILITY that I may allege against the Releasee, including attorney's fees, as a direct or indirect result of any injury to me or my property or resulting in any bodily harm, whether or not caused by any act or omission of Releasee, including but not limited to the negligence of Releasee or otherwise while I am in any way providing volunteer services on Site; (2) I CONSENT TO RECEIVE MEDICAL TREATMENT in the event that I become ill, I am injured or I am involved in an accident while on Site; and (3) I HAVE CAREFULLY READ, UNDERSTAND AND VOLUNTARILY SIGNED THIS AGREEMENT.

I HEREBY AFFIRM THAT I AM EIGHTEEN (18) YEARS OF AGE OR OLDER, I HAVE READ THIS DOCUMENT, AND I UNDERSTAND ITS CONTENTS.

Name:____ Date:_________________________

Address:____

Phone:____

Signature:____

Status Pending PolicyStat ID 21410094

Origination Date	04/2011	Department	Governance - AGOV
Last Approved	N/A	Applicabilities	System
Effective	Upon Approval		
Last Revised	09/2026		
Next Review	3 years after approval		

Peer Support (Care for the Caregiver), AGOV-1602

COPY

RISK:

Not having guidelines and structure for offering emotional support and mental health first aid to all adult employees who have been involved in, or witness to, a critical incident can lead to increased risk of stress which could affect employee performance and result in poor health outcomes for employees and patients.

POLICY:

A. Tahoe Forest Health System recognizes the potential emotional and psychological impact adverse, harmful and emotionally traumatic events can have on employees. We are committed to ensuring that comprehensive, organization wide support systems and care for all employees are available to those who may have been impacted by emotionally traumatic events.

B. Immediately following an event or critical incident an Operational Debriefing shall occur to identify immediate corrections needed to reduce any risk (e.g. processes, equipment) per policy, Operational Incident Debriefing, AQPI-1601. At that time, a referral may be made to deploy Peer Supporter(s) for adult employees needing emotional support services. This can include, but is not limited to, individual peer support, defusing or debriefing for the team, or further escalation through the Peer Support Algorithm. Peer Support is available to adult employees and contractors 18 years or older.

C. All Peer Support related referrals and encounters are maintained in a confidential manner. Specific areas throughout the Health System have been designated for Peer Support and are available at any time. These areas include the Quiet Room in Tahoe Forest Hospital Emergency

Department, the Community Room at Incline Village Community Hospital, Room Hotel 105 at Corporate ~~Point~~Pointe, and the Alpine Room at Pioneer Center.

D. The effectiveness and evaluation of TFHD's Peer Support is reported up through the Executive Sponsor of the program to the Administrative Council. Confidentiality of individual cases will be maintained throughout any evaluation process.

PROCEDURE:

A. The Peer Support team can be activated by anyone in response to a critical incident that triggers the need for emotional support of employees.

B. Activation of Peer Support will be accomplished by ~~contacting the House Supervisor, or any~~utilizing the Peer Support Module; a member of the Peer Support ~~team, who~~Steering Committee will then follow the Peer Support algorithm.

C. The Peer Support Algorithm (see attached) lists the variety of escalation options that may be needed, depending on the person/people who need emotional support in three tiers/levels. The algorithm will provide suggestions for the Peer Supporter that could be activated, based on the person needing support and the Peer ~~Supporters~~Supporter's position credentials.

D. ~~After the Peer Supporter has responded, he/she will complete a brief Quality/Safety Event, tagging the event as a Peer Support case for tracking purposes only. He/she will attach the confidential Peer Support encounter form within 72 hours of activation.~~

E. Evaluation of TFHD's Peer Support process will be achieved through ~~volume statistics (number and frequency of encounters) as well as some qualitative~~ data collection and analysis via the Peer Support Module. All individual evaluations will be kept confidential. Any demographic information collected on employees within the Peer Support Module will be automatically deleted seven days after the file is closed.

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Definitions:

A. **Adverse/ Harm event (aka critical incident):** An unanticipated event that may have or did result in harm. This could be a physical, psychological or financial event.

B. **Peer Support (aka Care for the Caregiver):** Emotional first aid provided to a person who is involved in an unexpected critical incident.

C. **Critical Incident**: Any reportable or non-reportable event that causes an unusually high level of stress for staff or events or situations that have sufficient emotional power to overcome the usual coping abilities of staff. A critical incident shall be defined by the person who experiences it, and not by outsiders. Each person has their own varying levels of resilience and ability to process a critical incident.

D. **Defusing:** Defusing is performed after the incident in a stable location. The purpose is to offer information, support, and allow initial ventilation of feelings, to set up or establish a need for a formal debriefing, and to stabilize staff members so they can go home or back to work. It is similar to a "mini" debriefing but is not as detailed or as long.

E. **Debriefing:** Debriefings are specially structured group meetings between the persons directly involved with the critical incident. It is a confidential, non-evaluative discussion of the involvement, thoughts, reactions and feelings resulting from the incident. It has psychological and educational components.

F. **Operational Debriefing:** Process of holding a post-event discussion about what happened during the event. The discussion may include input from participants regarding what occurred, what worked well, what could be improved upon. The operational debriefing should be based on process and facts. It is separate and apart from a peer supporter interaction (debriefing or defusing).

G. **Harm:** Any measurable amount of physical, psychological, or financial injury

H. **Peer supporter:** A trained member of the Peer Support Team who is trained in best practices and available to respond to the employee to offer and provide emotional first aid following a harm, adverse or emotionally traumatic event or critical incident.

I. **Traumatic event:** An experience in the workplace that causes emotional upheaval, or has the potential to impact the well-being of staff/employee(s) in the work environment. Examples of a traumatic event include but are not limited to the following:

1. Workplace violence event
2. Severe injury or death to a patient, employee, or visitor
3. Medical error
4. Unanticipated patient harm or death (especially when the age or other characteristics remind the individual of a family member or loved one)
5. Sudden loss of a co-worker
6. Collective, significant personal loss
7. Multiple deaths in a clinical area
8. Seriously troubled employee creating havoc with multiple staff members
9. Actual suicidal or homicidal attempts by a patient, employee, or visitor
10. Loss of positive coping skills, such as obvious addictions.

J. **Triggering event:** An adverse, unanticipated, or traumatic event.

Related Policies/Forms:

Sentinel/Adverse Event/Error or Unanticipated Outcome, AQPI-1906, Well Being Policy, MSGEN-9

All Revision Dates

09/2026, 11/2023, 10/2023, 05/2022, 06/2021, 05/2021, 06/2020, 12/2017, 02/2016, 11/2012

Attachments

TFHD Disclosure Checklist

TFHD Peer Support Activation Algorithm

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Approval Signatures

Step Description	Approver	Date
	Devon Kim: Executive Assistant	Pending

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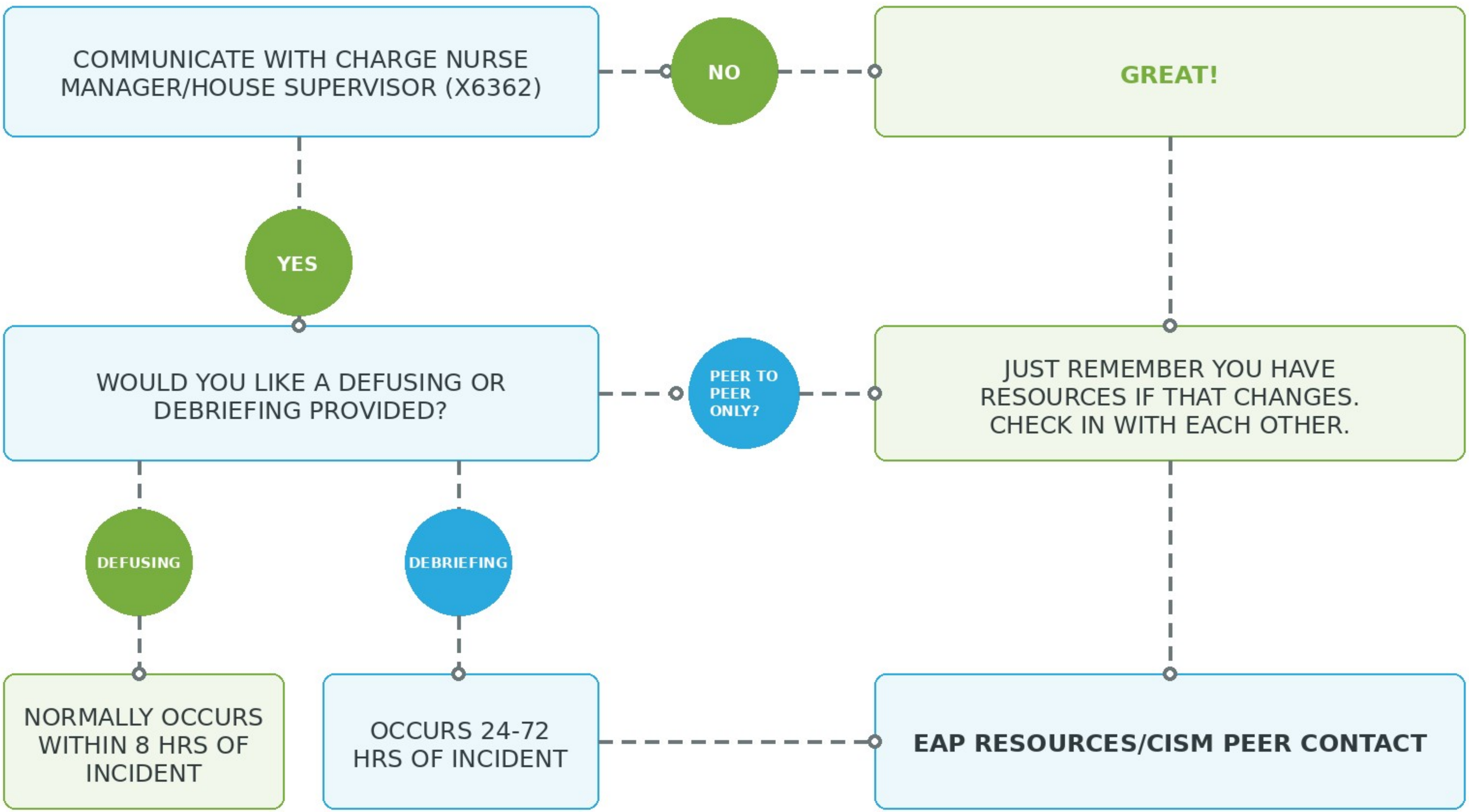
PEER SUPPORT

PEER SUPPORT TEAM ACTIVATION

CRITICAL INCIDENT IDENTIFIED



Charter

Quality Committee
Tahoe Forest Hospital District
Board of Directors

PURPOSE:
The purpose is to define the duties, responsibilities, and scope of authority of the Quality Committee.

RESPONSIBILITIES:
The Quality Committee serves as the standing committee of the Board of Directors, providing oversight of Quality Assessment and Performance Improvement (QAPI), assuring the delivery of high-quality care, promotes patient safety, and enhances the overall patient experience across the Health System.

DUTIES:
1. Recommend to the governing Board, action items and recommendations regarding any policies and procedures governing quality, patient safety, environmental safety, and performance improvement throughout the organization.
2. Assure the provision of organization-wide quality of care, treatment, and service provided and prioritization of performance improvement throughout the organization.
3. Steward the improvement of care, treatment, and services to ensure that it is safe, beneficial, patient-centered, customer-focused, timely, efficient, and equitable and it reflects the community.
4. Monitor the organization's performance in national quality measurement efforts, accreditation programs, and subsequent quality improvement activities adheres to the mission, vision, and values.
5. Whenever quality goals/benchmarks are not met, recommend corrective actions to the governing Board to address deficiencies, mitigate risks, and improve performance.
6. Ensure the development and implementation of ongoing board education, focusing on service excellence, performance improvement, risk reduction/safety enhancement, and healthcare outcomes.

COMPOSITION:
The Committee is comprised of at least two (2) board members as appointed by the Board Chair, the Medical Director of Quality, and Vice Chief of Staff or designee.

MEETING FREQUENCY:
The Committee shall meet quarterly.

REVISED 11/06/2025 – Approved by the TFHD Board of Directors 11/20/2025
No Changes 2026 – Approved by the TFHD Board of Directors 02/26/2026

Institute for Healthcare Improvement

Artificial Intelligence in Health Care

Implications for Patient and Workforce Safety

Innovation Report
ihi.org

Authors

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Patricia McGaffigan, RN, MS, CPPS, Vice President, IHI

This IHI innovation project was conducted from July to October 2023.

IHI's innovation process seeks to research innovative ideas, assess their potential for advancing quality improvement, and bring them to action. The process includes time-bound learning cycles (30, 60, or 90 days) to scan for innovative practices, test theories and new models, and synthesize the findings (in the form of the summary Innovation Report).

Acknowledgments

The authors are thankful to the interviewees who shared their insights, experiences, and expertise to inform this report. IHI is grateful to the Gordon and Betty Moore Foundation for their generous funding that supported this innovation project.

How to Cite This Document: Feske-Kirby K, Shojania K, McGaffigan P. *Artificial Intelligence in Health Care: Implications for Patient and Workforce Safety*. Boston: Institute for Healthcare Improvement; 2024. (Available at ihi.org)

Institute for Healthcare Improvement

For more than 30 years, the Institute for Healthcare Improvement (IHI) has used improvement science to advance and sustain better outcomes in health and health systems across the world. We bring awareness of safety and quality to millions, accelerate learning and the systematic improvement of care, develop solutions to previously intractable challenges, and mobilize health systems, communities, regions, and nations to reduce harm and deaths. We work in collaboration with the growing IHI community to spark bold, inventive ways to improve the health of individuals and populations. We generate optimism, harvest fresh ideas, and support anyone, anywhere who wants to profoundly change health and health care for the better. Learn more at ihi.org.

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Contents

Executive Summary

The excitement surrounding use of artificial intelligence (AI) in health care is palpable, especially for generative AI (genAI) tools such as ChatGPT. Yet, the specific potential benefits of such tools in health care, as well as the risks and unintended challenges potentially associated with their implementation, are not well understood.

To better understand the current landscape, the Institute for Healthcare Improvement (IHI) conducted a 90-day innovation project to identify high-level applications of genAI along with their advantages and disadvantages, including unexpected consequences or new safety hazards for patients and the health care workforce. The innovation project reviewed three primary types of clinical applications in health care: documentation support, clinical decision support, and chatbots that provide patient support.

While genAI applications in health care hold much promise, they also present serious potential risks that must be considered and addressed prior to more widespread implementation.

This report describes:

- A detailed review of three primary applications of genAI in health care: documentation support, clinical decision support, and chatbots that provide patient support;
- Analysis and review of the three genAI applications — including functions, benefits, risks, and examples — relevant to inpatient, primary care, and ambulatory care settings;
- Potential patient safety risks and unintended consequences resulting from genAI tools; and
- Considerations and recommendations for ongoing work to finetune AI tools and mitigate potential risks.

Intent and Aim

In May 2023, the Institute for Healthcare Improvement (IHI) Lucian Leape Institute identified artificial intelligence (AI), specifically generative AI (genAI), and safety considerations for applications in health care as an area of interest to further investigate. The intent of this IHI 90-day innovation project (conducted from July to October 2023) was to identify the high-level applications of generative AI in health care and assess implications for safety, including unexpected consequences or new safety hazards for patients and the health care workforce. Generative AI includes machine learning systems capable of generating text, images, code, or other types of content, often in response to a prompt or question entered by a user through a chat interface.

With the proliferation of AI and generative AI applications in health care, it is necessary to examine how to appropriately integrate these technologies into clinical workflows and health care operations with careful attention to the impact on patient care and safety, workforce safety and well-being, and the health care sector as a whole. There are also considerations for the rapid adoption of this technology, which may outpace the education and agility of the workforce as well as existing technological infrastructure.

The 90-day innovation project included these activities:

- Literature scan to analyze current and future uses of AI, particularly generative AI, in health care: This included literature on generalized perspectives of the use and risk of AI in health care and publications specific to various health care settings and specialties.
- Interviews with 27 individuals from selected health care and other organizations to gain further insights: This included academic experts, practitioners, and technical experts with relevant expertise in the topic area.

The innovation project reviewed three primary types of clinical applications in health care (see Table 1) and focused on generative AI tools already available for implementation and those likely to find application in clinical care within the next year.

Table 1. Generative AI Applications in Health Care

GenAI Application	Description
Documentation support	Functions include producing formatted visit or encounter notes from transcripts of patient-clinician interactions. Other examples include generating discharge summaries from the notes and results in the electronic health record (EHR), summarizing patient information (e.g., for handovers), and resolving inaccuracies and redundancies in the EHR.
Clinical decision support	Functions include providing diagnostic support by providing potential diagnosis based on symptoms, test and lab results, and patient history; providing early detection or warning on patient condition; and developing potential treatment plans.

Chatbots	Functions include personalized patient communication and navigation services, particularly supporting clinicians in responding to messages from patients in EHR inboxes.
Additional non-clinical uses (see Appendix B)	Includes administrative assistance (e.g., medical billing and coding), as well as support for medical research and education, and quality improvement (QI) and safety efforts (e.g., preparing case summaries for root cause analyses).

The aim of this innovation project is to inform health care personnel about the specific functions genAI tools in health care can accomplish — now or in the immediate future — while also identifying potential risks and mitigation strategies.

Background

With the emergence of publicly available AI chatbots such as OpenAI's ChatGPT (GPT-3.5, GPT-4) and Google's Bard, AI applications in health care are rapidly growing. While not yet widely applied in practice, published reports have already shown that generative AI tools can pass medical licensing examinations, generate clinical notes, and respond empathetically and accurately to medical questions from patients.[1,2,3,4] These and other applications, such as point-of-care decision support for diagnosis and treatment, have understandably generated widespread excitement.

Yet, this growing interest in implementing genAI tools in health care coincides with calls from prominent AI experts to pause the development and implementation of AI applications for varied concerns, including accuracy, the perpetuation of systemic biases, spreading disinformation, privacy and security threats, and fears about the negative implications for the human workforce and the existential threat of AI developing autonomously.

One concrete example of concerns over accuracy consists of so-called "hallucinations" or "confabulations" — that is, false or made-up statements presented as factual (see Table 2 and Appendix A for terminology and definitions). Non-medical examples of such hallucinations have appeared in the news, such as the example of a legal firm that submitted a brief containing non-existent legal precedents.[5] Examples of chatbots making up medical citations also exist.[6] In one article about using GPT-4, an AI-generated medical note presents the patient's Body Medicine Index (BMI) as a specific value despite the lack of supporting information from the original clinical encounter note.[7] As the article authors noted, "such errors can be particularly dangerous in medical scenarios because the errors or falsehoods can be subtle and are often stated by the chatbot in such a convincing manner that the person making the query may be convinced of its veracity."[8]

In addition to the issue of hallucinations and confabulations, there remain many problems involving the perpetuation of social biases and inequities that are often baked into the datasets used by genAI applications.[9,10,11,12,13] For instance, AI tools used to diagnose skin conditions may have been trained on datasets without sufficient representation of the variation in common skin diseases (never mind rare ones) across different skin types, especially people with darker skin tones.[14] Insufficient representation in training datasets can also lead to AI tools missing the presence of disease in chest radiographs of patients from racialized or underserved groups.[15]

Artificial intelligence is not new to health care. Early expert systems for medical diagnosis emerged in the 1960s followed by the development of early applications for image recognition and diagnosis in the 1970s and the use of natural language processing for documentation in the 1990s.[16,17] More recent years (circa 2016) saw machine learning programs akin to those used to beat world champions in chess and demonstrate expert-level performance in interpreting medical images in radiology, pathology, and dermatology.[18,19,20,21]

These algorithms and models differ, though, from contemporary genAI in that they were typically trained on large datasets containing "gold standard judgments" by human experts (e.g., tens of thousands of moles clearly identified by majority consensus among dermatologists as either benign or malignant). These models also tend to have known performance in terms of the accuracy of their specific judgments (e.g., if a skin lesion not from the training dataset is benign or malignant).

GenAI tools have the advantage of not being so focused — they can make judgments or provide answers in response to questions or prompts for which they were not specifically trained. On the other hand, they were trained on datasets with no "gold standard" answers. For instance, there may be numerous images and text materials related to moles, but no human experts have verified the veracity of the statements contained in these materials. The performance of the AI tools in terms of generating accurate answers has thus far been assessed mostly at a general level (e.g., not in terms of arriving at the correct diagnosis or treatment recommendation for specific clinical situations).

Table 2. Terminology and Definitions

Term	Definition
Artificial intelligence (AI)	The branch of computer science that aims to create systems capable of performing tasks that typically require human intelligence.[22] These tasks can include problem-solving, understanding natural language, recognizing patterns, making decisions, and adapting to new information. AI systems can be based on rules and algorithms or can be trained using data-driven approaches like machine learning, where they improve over time by learning from data.
Big data	An indetermined phrase that often refers to a large, diverse, and complex set of data from various sources. Authors of one article note that there is no agreed on standard definition, although there are important overlaps recognized in the definition above.[23]
Generative artificial intelligence (genAI)	Broadly speaking, generative AI refers to machine learning systems capable of generating text, images, code, or other types of content, often in response to a prompt or question entered by a user through a chat interface. This differs from discriminative AI models that perform

	functions such as data classification or data grouping, or action oriented.[24] GenAI models are initially trained on broad datasets (e.g., massive amounts of text from the Internet), then the model is finetuned, often with a more specific or specialized dataset (e.g., text relevant to health care), in which human reviewers refine the model's behavior and ensure that it aligns with intended use cases and ethical guidelines.[25] Generative artificial intelligence systems include large language models as well as image generators, code generator tools, and auto generation.[26] Prominent commercial examples of gen AI models include OpenAI ChatGPT, Google Bard, and Llama 2 created by Meta.
Generative pretrained transformer (GPT)	AI that can produce human-like writing such as ChatGPT.[27]
Hallucinations or confabulations	False or made-up statements presented as factual.
Large language models (LLMs)	A type of AI that engages with language. These models are referred to as "large" due to the increase in parameters for training language models, including increased data and computational power.[28] Large language models may also be called foundational models.
Machine learning (ML)	Machine learning is a subfield of artificial intelligence that uses algorithms trained on datasets to create models that enable machines to perform tasks that would otherwise only be possible for humans.[29]
Natural language processing (NLP)	A type of speech recognition AI focused on producing human-like language processes and outputs using text and spoken word through a computer.[30,31] Functions range from simple analytics tasks like classifying documents to advanced tasks like responding to questions and summarizing literature.
Neural network	Computing systems with interconnected nodes that can identify hidden patterns and correlations in raw data. These patterns and correlations are clustered and classified and, over time, the system can continue to learn and improve.[32] Multilayered neural networks constitute the "deep learning" programs used for medical image interpretation, among other applications.
Transformer model architecture	A neural network algorithm that learns contextual information from sequential data (e.g., wearables, videos, textual works in written or spoken language, or other audio signals).[33] Transformer model architecture is the basis for large learning models.[34]

Generative AI in Health Care

The excitement over AI in health care reflects its potential to achieve several distinct goals. AI-powered decision support tools will almost certainly increase the proportion of patients receiving accurate diagnoses and evidence-based treatments. These tools may also foster earlier recognition of deteriorating patients and play a role in reducing common, preventable adverse events as well as address other patient safety and quality of care issues. Existing genAI tools can facilitate clinical documentation and administrative tasks that contribute to clinician burnout. There also are genAI tools that can produce patient-facing versions of complex medical notes, answer medical questions for patients, and provide substantial assistance with care coordination and patient navigation.

With many potential genAI applications in health care — which vary based on technologic simplicity or complexity and readiness for adoption[35] — the field must proceed with caution since most AI tools have not undergone evaluation or validation to assess their accuracy or the extent of adverse consequences. Notable concerns include the problem of authoritative-looking pronouncements containing factually incorrect material (i.e., hallucinations, confabulations), misleading or inappropriate outputs due to biased training sets, and various ethical, legal, and regulatory concerns (e.g., the need for FDA/regulatory oversight of AI tools that amount to medical devices), among others.[36,37,38]

The combination of massive potential benefits accompanied by numerous serious unintended consequences place health care workers, executives, and consumers in a bind. Numerous genAI tools offer promise for making clinicians' work much easier (e.g., instantly generating medical notes from patient-provider interactions) and value for patients (e.g., instantly generating patient-friendly versions of medical notes and enabling clinicians to provide timely and better care).

On the other hand, implementing these tools could lead to massive, irreversible new problems. As a corollary, electronic health records (EHRs) were also supposed to make clinicians' lives easier, when many cite the EHR "solution" makes the work more complex and inefficient.[39] Yet, one of the main arguments in favor of AI tools is that they will help address the problem of clinician burnout widely attributed to EHRs.

Results of the 90-Day Innovation Project

The landscape of AI in health care is highly dynamic, rapidly expanding and changing, including the state of technology developments, the implications for our knowledge of how well AI tools perform, and related safety implications. Consequently, we caution readers that this report may be dated by the time of publication or shortly thereafter. Additionally, the findings from the literature review and interviews during this innovation project reveal a lack of expert consensus on application readiness, notable risks or challenges, and conflicting viewpoints.

Even with the enthusiasm surrounding AI in health care, the promise must first be examined. What applications are ready to go? How, where, and with whom should they be designed and implemented? What are the benefits, risks, and implications of using specific AI applications?

The findings in this report primarily focus on applications and uses of AI, particularly generative AI, for clinical care delivery systems. This report addresses three primary genAI clinical applications: documentation support, clinical decision support, and chatbots that provide patient support. Analysis and review of each AI application includes functions, benefits, risks, and real-world examples and are relevant to multiple care settings, including inpatient, primary care, and ambulatory care.

The report provides real-world examples of AI applications in development or implementation. Any references to information and technology companies and health care system partnerships are not an endorsement of said companies or partnerships; it was beyond the scope of the innovation project to validate or test related applications.

Please see Appendix A for a description of risks, challenges, and unintended consequences of clinical applications of genAI, and Appendix B for details on non-clinical uses of genAI technology in health care.

Review of Three Clinical Applications of GenAI

1. Documentation Support

- Produce Patient Interaction Notes
- Produce Patient Medical History Summaries
- Resolve Patient Record Inaccuracies and Redundancies
- Provide Accessible Patient-Facing Documentation

2. Clinical Decision Support

- Suggest Potential Diagnoses
- Provide Early Detection or Warning
- Propose Treatment Plans

3. Chatbots That Provide Patient Support

- Patient Communication
- Triage Patient Check-In and Information

Review of Three Clinical Applications of GenAI

This section discusses three clinical applications of genAI: documentation support, clinical decision support, and chatbots that provide patient support. Table 3 at the end of this section provides a summary review of these applications and potential risks.

1. Documentation Support

A key application of genAI is documentation support. Currently, clinical documentation is typically entered into electronic health records (EHRs) by clinicians or clinical support staff such as scribes. Yet, this manual effort can be burdensome, time-intensive, and is frequently cited as a major contributor to clinician burnout.[40,41,42] The use of genAI for documentation support has multiple functions and can be used to support both patients and clinicians.

Clinicians can utilize genAI applications for a broad array of documentation support purposes, including to:

- Record visit or encounter notes during patient-clinician interactions;
- Summarize patient information including demographics, medical history, and medical records; and
- Resolve inaccuracies and redundancies in a patient's electronic health record.

Produce Patient Interaction Notes

Using ambient listening, genAI can produce detailed and accurate notes of patient interactions, including scheduled care visits and bedside visits.[43] Early adopters have begun using AI technology in multiple settings, including primary care, ambulatory care, and the emergency department.[44,45,46] While genAI can produce the note, clinical oversight is needed to both review and edit the note prior to completion. In fact, one expert from a large health system shared that their organization had deliberately designed their AI-powered scribe tool to generate notes with features indicating that notes are only approximately 90 percent complete, so that clinicians must review and provide final input to publish a completed note.

Using AI-powered scribe tools during clinical encounters involving multiple speakers (e.g., patient, family members, and clinician or a patient and several clinicians) is still a work in progress. Ambient noise associated with inpatient encounters (e.g., in the emergency department or an intensive care unit) may also present problems for AI-driven scribe tools, although improvements to mitigate such issues are actively being addressed by some tools.

Produce Patient Medical History Summaries

GenAI can provide clinicians with succinct summaries of a patient's medical history, including reasons for patient visits, previous clinical encounter notes (including primary care or specialist visits), charting for inpatient patients, and previous labs or imaging. Patient summaries have multiple uses such as reducing clinical time spent creating and reviewing patients notes or reviewing patient history during a visit, improving communication for clinical handoffs or referrals, and ensuring continuity in clinical care delivery.

Resolve Patient Record Inaccuracies and Redundancies

GenAI can be used to resolve inaccuracies and redundancies in a patient's electronic health record (EHR). While not discussed as thoroughly in the literature, interviewed experts suggested that genAI technology could be applied to patient EHRs to improve the quality of notes by removing inaccuracies and reducing redundant notes. While less studied than other genAI applications, ensuring that electronic clinical documentation is accurate and accessible not only improves record keeping, but also provides higher quality data for clinical encounters and for use in de-identified datasets.

Provide Accessible Patient-Facing Documentation

GenAI can produce patient-facing documentation — accessible material provided to the patient that details specific health care-related information. GenAI applications could efficiently create visit notes, discharge summaries, and treatment plans in simple language (or at the reading proficiency level of the patient and/or approved caregiver), removing clinical or medical jargon without decreasing the accuracy of information. Additionally, it's possible for genAI tools to provide language translations of patient notes, records, and resources to advance equitable care for patients who speak a different primary language.

Potential Benefits and Risks

The use of genAI to support clinical documentation has notable benefits:

- Reduce documentation burden for clinicians;
- Increase clinical time available for direct patient care; and
- Improve accessibility for patients, given that AI tools can produce patient-friendly versions of medical notes in multiple languages.

What is not yet known is how often genAI tools produce inaccurate statements within such notes. Some experts indicated that, apart from input errors (e.g., incorrectly transcribed words due to ambient noise or unfamiliar accents), AI-generated content that is factually incorrect (i.e., hallucinations or confabulations) is rare. Other interviewed experts highlighted that hallucinations can happen whenever a genAI tool analyzes or synthesizes information, which can also occur with producing formatted clinical notes and not just transcriptions of the verbal interaction.[47] If AI programs produce inaccurate outputs, that documentation's accuracy could be further diluted due to recall bias by the provider(s).

Additional risks that may be encountered with genAI applications for documentation support are described below.

- **Deskilling:** Clinicians, especially those early in their career, may lose the ability to synthesize and concisely summarize the key information obtained during exchanges with patients.
- **Patient privacy and data rights:** Chatbots have already produced privacy scandals.[48] In March 2023, a software glitch allowed ChatGPT users to see queries posed by others and in some cases could see their credit card information.[49] The authors of one article assert, with the limited privacy and data protection laws in the United States and

technological advancements such as the EHR, "HIPAA's Privacy Rule is based on a fallacy: the belief that data can be successfully stripped of personal information (de-identified) and that doing so renders it safe. In the age of LLMs, data can easily be re-identified, and even de-identified data can cause significant harm."[50]

- **Patient preference:** Some patients may perceive use of AI technology as an intrusion and threat to privacy, though others may welcome clinicians not having to focus so much on computer screens during clinical encounters.
- **Application errors:** Hallucinations and confabulations in AI-produced content have already been mentioned, and there may be other AI-generated errors related to the quality of the ambient audio in different and difficult clinical settings with multiple participants and/or noise.

Examples

Despite these concerns, medical documentation facilitated by generative AI tools is already proceeding, as the following examples illustrate.

- As of 2023 Houston Methodist is applying Pieces technology to provide a "working summary" for clinical handovers to improve patient care quality, reduce documentation burden, and improve clinical communication.[51] The working summary in the acute setting includes patient demographics, patient condition (current and recent), relevant patient history, recent procedures, predictive discharge status, and contextual risk assessment and communication.
- In 2023, HCA Healthcare partnered with Augmedix to accelerate the development of AI-enabled ambient documentation solutions for acute care providers.[52] Clinicians can use the Augmedix app to create hands-free, precise, and timely medical notes from clinician-patient interactions. The proprietary platform leverages NLP (in addition to Google Cloud's genAI technology, which HCA Healthcare is also partnered with, and multi-party medical speech-to-text processing) to promptly convert the collected data into medical notes, which clinicians review and finalize prior to transfer into the EHR.[53]
- As part of their Partners and Pals program, Epic, the developer and vendor of electronic health records, has named their first Pal, Abridge, a leading company in genAI for clinical documentation.[54] Through this collaboration, Epic and Abridge plan to help providers focus on patients and reduce time spent on documentation, help patients better understand their conversations with providers, and help health care systems rapidly adopt genAI-based solutions. Emory Health will be leveraging this partnership, announcing an enterprise-wide agreement to make Abridge's Epic-integrated genAI solution available to clinicians over the next three years.[55] Emory will join the University of Pittsburgh Medical Center (UPMC) and the University of Kansas Health System in using Abridge through Epic EHR.[56]

2. Clinical Decision Support

The use of clinical decisions support (CDS) in health care is not novel, but genAI could advance CDS tools. Traditional CDS consisted of software designed for a specific purpose to directly aid clinical decision-making. This traditional rule-based application has changed over time with the advancement of technology, with CDS increasingly developing the capacity to leverage data and observations independently (e.g., AI and genAI solutions).[57]

As CDS aims to inform clinicians' decisions about patient care to improve patient outcomes, thereby leading to higher-quality health care, AI applications can support clinical decision-making through the following functions:

- Provide diagnostic support by suggesting potential diagnoses to explain the constellation of symptoms and test results for a given patient, as well as diagnostic support for interpreting medical images;
- Provide early detection or warning on changes to patient condition, including risk assessment and suggested interventions; and
- Develop potential treatment plans, including suggested medications and tests.

Suggest Potential Diagnoses

A genAI application could suggest diagnoses to consider based on presenting symptoms and clinical assessment. To have a sense of how well genAI technology performs in this regard, one research group evaluated ChatGPT's diagnostic performance on 36 clinical vignettes. The researchers characterized its performance as on par with the level of an intern or resident, with 77 percent accuracy on final diagnosis, 68 percent accuracy on clinical management decisions, and 60 percent accuracy on differential diagnoses.[58]

In another example, researchers assessed the performance of Chat GPT-4 in suggesting the correct diagnosis for cases presented as clinicopathologic conferences in the *New England Journal of Medicine.* The genAI model's leading diagnosis agreed with the final diagnosis in 39 percent of cases; in 64 percent of cases, the model listed the final diagnosis in its so-called differential diagnosis.[59]

These results attest to the impressive ability of genAI tools to digest disparate elements of a complex medical case and suggest the correct diagnosis or differential diagnoses for the clinician to consider. Yet, they also highlight the potential problem of automation bias, which raises the risk of diagnostic error and clinician complacency. Clinicians must not defer, consciously or subconsciously, to the AI tool's suggested diagnosis without considering alternatives — at least not with the current approximately 25 to 35 percent inaccuracy of these suggestions, based on available evidence. While many experts expressed enthusiasm for AI-powered decision support, most acknowledged that accuracy needs to improve — as well as establishing reliable performance in a robust manner — to justify widespread implementation.

Provide Early Detection or Warning

While more simple rules-based decision support has been used for clinical decision support for many years, genAI could further support the refinement and expansion of early detection and warning systems. GenAI can support predictive analytics for earlier detection of deteriorating patient conditions and support predicting patient risk for contracting certain conditions or predicting patient likelihood of responding to treatment.[60,61] As noted in the "Documentation Support" section above, early detection and warnings can also be included in clinical documentation (see Houston Methodist example).

Propose Treatment Plans

GenAI could act as a CDS tool by proposing a suggested treatment plan that includes potential medication, appointment follow-ups, referrals, a care plan, and patient education. These recommendations would be based on a patient's medical history, genetic information, and lifestyle and behavioral factors.[62] Clinicians would be required to review and alter the treatment plan as needed to meet the patient's needs and preferences. As with diagnostic decision support, though, the performance characteristics of such AI-generated recommendations have yet to be established as suitably accurate for clinical application.

Potential Benefits and Risks

To be clear, genAI-powered CDS tools aimed at specific conditions will undoubtedly undergo evaluation and be shown to perform well (e.g., see Intermountain Health example below). Yet, decision support focused on specific conditions differs from the more general decision support envisioned for the years to come, in which AI-driven programs will make diagnostic and therapeutic suggestions related to whatever condition seems suggested by the content of the clinical note the user has opened. For example, "It looks like your patient has 'X' illness. You should consider initiating the following medications…." — where "X" might include common conditions such as diabetes or pneumonia, but also much less common diagnoses.

One key risk associated with AI clinical decision support relates to biased or incomplete training datasets such that AI model outputs are less accurate for patients from different racial/ethnic backgrounds. For instance, one of the experts we interviewed mentioned asking an AI chatbot the most likely diagnosis for a man in his 20s with sore throat and swollen lymph nodes in the neck. For a white patient, the suggested diagnosis was infectious mononucleosis. When the race was changed to Black, gonococcal pharyngitis (i.e., a sexually transmitted disease) was offered as a diagnosis to consider even though it had not been mentioned when a patient was labeled as white. As one expert noted, the diagnostic suggestions provided by AI tools reflect probabilities based on what has been said online ("the epidemiology of the Internet") and not on the actual epidemiology of disease for relevant patient populations.

One journal article provides another example of racially biased recommendations from a genAI tool. The authors asked ChatGPT about the most appropriate analgesia for a 50-year-old man presenting to the emergency department with chest pain. When the man's race was white, ChatGPT recommended "a strong opioid, such as morphine or fentanyl." When the race was changed to Black, ChatGPT stated that the appropriate choice depended on the cause of the chest pain (a qualification not made for the white patient) and then went on to recommend a non-steroidal anti-inflammatory such as ibuprofen or naproxen. As previously mentioned, biased datasets can also affect the accuracy of AI-based diagnosis of radiographs and skin lesions.[63]

It is also worth noting that decision support typically takes the form of pop-up alerts and reminders, and these have generally had as many failures as successes, with the average effect consisting of small improvements in the percentages of patients receiving recommended care.[64] There is also the issue of alert fatigue due to alerts too often firing inappropriately. Some older rules-based decision support tools have often had false positive rates of 90 percent or higher.[65,66] In another study, an AI-driven pneumonia decision support tool had a lower false positive rate of 50 percent.[67] But a false alarm rate of 50 percent may still contribute to patient harm and burnout when clinicians are seeing multiple other forms of decision support, each with their own false alarm rates.

Finally, even if there are reasonable grounds for excitement over high-performing AI-driven decision support tools becoming available soon, fraudulent overpromising has also occurred. For instance, Babylon Health, a UK start-up claiming to put AI tools to work to "put an accessible and affordable health service in the hands of every person on earth," went from rapid expansion and being lauded in 2019 to shuttering its US headquarters in 2023.[68,69]

Example

- Intermountain Health is rolling out the ePneumonia app to all hospitals and urgent cares in seven states as announced in spring 2023.[70] Using an AI Bayesian network, the application helps clinicians determine the best course of treatment for patients and has showed improved outcomes for patients with pneumonia in a randomized controlled clinical trial in 16 community hospitals.[71]

3. Chatbots That Provide Patient Support

A popular, mainstream application of genAI, chatbots could also play a role in supporting communication with patients and managing clinical intake. While all genAI applications must be compliant with regulations such as the Health Insurance Portability and Accountability Act (HIPAA), functions could include:

- Personalized patient communication; and
- Triaging patient check-in information for in-person clinical care settings.

Patient Communication

Personalized patient communication via AI tools can occur both online and in person. Many experts anticipate using AI tools to respond to patient inquiries through online patient portals, provide patients with answers to basic medical questions, or support management plans, particularly for patients with chronic illnesses.[72,73] In-person AI applications for communication might include virtual chatbots available to patients that answer basic questions, set reminders, and facilitate communication with the care team.[74]

Similar to non-automated messages, clinicians will need to review drafts crafted by chatbots (then decide to modify or leave the draft as is, or create a unique response), but this AI application could still reduce the time spent on responses, particularly if the draft includes accurate and appropriate medical information. Moreover, like patient-facing documentation, patient-oriented chatbots could also communicate in simple language (or at the patient's reading proficiency level) as well as provide language translation for patients.

Triage Patient Check-In and Information

While chatbots may already assist prior to an appointment by supporting timely check-in in ambulatory care, urgent care, or emergency department settings, there is potential for genAI to triage patient information prior to a patient-clinician interaction.[75] Chatbot-supported check-in could collect basic information on the patient, including reason for visit and patient history, and synthesize this information along with a patient's existing medical history to provide a triaged assessment of the patient for the provider to review prior to the encounter.

Potential Benefits and Risks

The use of chatbots for patient communication and triaging could reduce clinical workforce burden, especially EHR inboxes overflowing with patient messages awaiting responses. The use of AI support tools can also lead to quicker response times for simple patient questions and more personalized patient-clinician communication, which may improve the patient care experience.

One study has shown that chatbots can answer questions from patients with comparable quality to answers generated by physicians — and, perhaps because the chatbot does not fatigue or uses standardized language, its responses were judged by patients as more empathic than clinicians.[76] Yet, these AI applications will also contain some hallucinations and other errors, so health care organizations will need to consider strategies to audit the accuracy of applications. Even when implementation includes a step for clinicians to edit AI-generated responses to patients, there will be a natural tendency for many clinicians to omit this step — a concern raised by many interviewed experts, which is also relevant for AI-generated medical notes. Organizations may need to engage a cadre of clinicians who volunteer to critically review chatbot messages to patients to identify the true frequency of incorrect or misleading answers.

Further, messages must be edited by clinicians prior to dissemination to confirm accuracy and credibility and ensure that the response is unique to the patient's concerns, questions, conditions, and preference, including accessibility (e.g., use of simple language, provided in the primary language of the patient). Poor communication through the chatbot could negatively affect patient-provider relationships such as the patient or provider mistrusting one another or the technology. This is why the chatbot must be tested and validated by adequately skilled users who verify the accuracy of the AI-generated information. If automatic messages are utilized, health care systems may need to consider using disclaimers for liability purposes.

Example

- In the summer of 2023, UNC Health began piloting Epic's AI tool, Inbasket, which drafts clinician responses to patient's questions or comments and aims to reduce administrative burdens for staff.[77] Through this pilot test, UNC Health aimed to keep clinicians in the loop with new AI tools and hoped to offer a friendly introduction to AI tools for patients and clinicians with the reminder that AI is there to help and not replace clinicians. Additionally, while not a patient-facing application, in June 2023, UNC Health announced the rollout of an internal chatbot tool for a small group of clinicians and administrators, with plans to offer it more broadly at a later date.[78]

Table 3. Generative AI Clinical Applications and Potential Risks

Note that not all potential risks and challenges are accounted for in the table.

GenAI Application	Description	Potential Risks and Challenges
Documentation support and scribe function	• Record visit or encounter notes during patient-clinician interactions • Summarize patient information including demographics, medical history, and medical records • Resolve inaccuracies and redundancies in a patient's electronic health record	• Errors caused by ambient noise or multiple speakers • Factually incorrect information ("hallucinations") • Need for local calibration or performance testing • Clinical deskilling (e.g., automation bias, complacency) • Patient privacy and data rights (e.g., data retention policy)
Clinical decision support	• Provide diagnostic support in identifying potential diagnoses and reducing diagnostic error, including improvements in imaging analysis • Deliver early detection on patient condition, including deterioration, and risk assessment • Serve as a virtual assistant to clinicians during treatment • Develop potential treatment plans, including suggested medications and tests	• Unknown performance for most current AI applications • Clinical overreliance and deskilling • Biased datasets leading to inappropriate output for patients from racialized or underserved groups • Worsening alert fatigue
Chatbots that provide patient support	• Provide personalized patient communication • Triage patient check-in and synthesize check-in information for in-person clinical care settings	• Inaccurate data or responses • Patient preference to interact with humans and/or avoid use of these tools • Lack of accessibility for some patients due to lack of facility with using chatbots • Falsehood mimicry and need for adequately skilled user • Poor performance could lead to mistrust of technology or providers

Future Considerations

With heightened excitement, expectations, and rapid adoption of genAI tools in health care, how do we further emphasize caution and safety in this ever-growing space to ensure that patient and workforce safety and other considerations remain at the forefront of consideration, and are not overshadowed?

Begin with Governance

The experts that IHI interviewed emphasized that health care organizations need to begin by building and fortifying governance structures and policies pertaining to genAI. This could include either creating a new governance or oversight body or by tasking a related, existing body with AI governance.

Regardless of where the oversight structure is located within a health care system, it is important to begin efforts by designating a system leader with responsibility for AI activities and ensuring that any oversight body includes a cross-functional team with staff from various roles and responsibilities.[79] This can include executive leaders; clinical representatives; end users (including physicians, nurses, pharmacists, safety/quality/risk leaders, patient and family advisors, administrative or operational staff), IT staff, and members with AI expertise (which could be an external partner if the health system lacks the appropriate internal expertise).

Following the development of a governance body, organizations need to take these steps:

- Develop a clear organizational approach for AI integration that aligns with existing system goals and objectives;
- Improve AI literacy for governance members and staff, including foundational education on AI, applications in health care,

Begin with Governance

- Establish a clear and intentional organizational strategy to support a coordinated approach to AI implementation.
- Create guardrails to ensure the appropriate, effective use of AI applications.
- Conduct a critical assessment of system needs, readiness, and capacity.

Proceed with Caution

- Ensure that genAI models are validated, regulated, and monitored for quality, safety, and ethics.
- Remain up to date on regulations and on collaborative efforts to standardize and develop guidelines and guardrails.

Start Simple and Meet End Users' Needs

- Ensure that AI applications are in the best interests of ensuring patient safety.
- Communicate and engage staff in organizational genAI efforts.

design and implementation risks, and relevant regulatory guidance;

- Develop decision, testing, workflow, and support criteria to inform selection, vetting, value, and ongoing support of AI solutions;
- Create guardrails with safety management systems that include measurement and monitoring plans to ensure that AI is used safely, effectively, and equitably within the organization;
- Ensure that the benefits and risks of AI solutions for specific use cases are clearly defined and addressed prior to use; and
- Review existing operations and infrastructure to determine the health system's current capacity and identify potential improvements and investments needed to integrate AI.

Establish a clear and intentional organizational strategy to support a coordinated approach to AI considerations and potential implementation.

This strategy needs to align with a health care system's existing goals and objectives to ensure continuity in organizational vision. Through this process, systems can further establish priorities and processes prior to AI design and implementation to ensure a systematic and transparent approach to AI integration into health care delivery. Developing an informed and cohesive strategy, though, can be challenging in a rapidly changing technology and regulatory landscape, so it is important that governance members, as well as staff and end users, are educated and gain proficiency in AI in two aspects: 1) gain foundational knowledge on how AI is developed and how it functions, and 2) understand the applications and risks of the technology in a health care setting.[80] Organizations can provide learning opportunities through training sessions or tutorials, brainstorming sessions, and hands-on experiences in a controlled setting (e.g., application sandboxes or simulations). Additionally, an organization's workforce must be apprised of the organizational approach to AI, once identified, and involved in the co-design and implementation of genAI technology.

Create guardrails to ensure the appropriate and effective use of AI applications.

Develop rigorous evaluation methods and assessment frameworks for AI applications, audit tools for applications and datasets, as well as workforce feedback mechanisms such as user groups.[81] Safety guidelines must be detailed, including warnings on AI application risks, reminders of patient privacy (e.g., not sharing patient information on open-source AI), and emphasizing that AI tools must be used in accordance with accepted standards of care and conform with regulatory standards and guidance; following the accepted standard of care can reduce the likelihood of patient harm and liability for clinicians and health care delivery organizations.[82]

Conduct a critical assessment of system needs, readiness, and capacity.

Health care systems seeking to integrate AI must first assess their needs.

- Ask clinicians and staff what problems they need solved to guarantee that any new technology is relevant (e.g., asking, "What is important to you for the organization to improve?" or "What is a major pain point in your daily workflow?").
- Ensure outreach to a diverse group of employees with various roles and responsibilities for input.
- Reflect on whether identified issues or solutions align with the organizational vision or aims. Note that, if a need identified by staff does not align with an organization's aims or vision, this does not mean the need should be disregarded; this could serve as an opportunity for the organization to assess whether or not the aims or vision are also meeting workforce needs.

Assessing for system capacity specifically refers to a health care system's IT infrastructure. This assessment should aim to answer questions such as:

- What is the current capacity of a health care system IT and data infrastructures?
- What types of AI implementations can the infrastructure support in its current state?
- Is the necessary expertise and talent onboard or able to be resourced to support system and end user needs?
- Have data fidelity and accuracy needs been assessed to determine whether it is fit for use with AI tools?
- Do we understand data risks and do we have the necessary infrastructure to ensure protection of data?
- What improvements and investments are needed to ensure the system can function with new AI applications, if any?

These suggested steps in developing a governance framework for AI applications are not linear or comprehensive. Interested organizations are encouraged to review other sources — such as Duke Health AI's Algorithm-Based Clinical Decision Support Oversight[83] or a proposed governance model for AI in health care[84] — and establish learning system practices across their organization and with other organizations.

Proceed with Caution

It is critical to remember that many genAI models are not ready for full-scale deployment in a clinical care delivery setting. As our research and interviews reveal, and as the World Health Organization acknowledged,[85] while many are enthusiastic about the use of these technologies, there are varying opinions and concerns about the level of caution that is being exercised. Risk identification and mitigation is key to using AI-based applications in health care and, with a rapidly changing technological landscape, interested parties need to demonstrate restraint and prioritize an ongoing commitment to patient and workforce safety and quality.[86]

Health care systems need to exercise care when considering and adopting genAI in clinical care settings (as well as non-clinical settings), with attention to research and testing to ensure that genAI models are validated, regulated, and monitored for quality, safety, and ethics. This includes remaining up to date on collaborative efforts to standardize and develop guidelines and guardrails to promote the fair use of AI systems in health care, such as the National Academy of Medicine's Artificial Intelligence Code of Conduct[87] and the Coalition for Health AI (CHAI).[88]

Organizations must also remain current on pending and authorized regulations at multiple levels. For example, the US Food and Drug Administration released draft guidance tailored to AI- and ML-enabled devices as they further develop a regulatory approach to protect patients and increase the effectiveness of devices.[89] Using caution and staying aware of the regulatory landscape can ensure that patients and the health care workforce do not bear the burden of poorly executed design, implementation, or integration of AI applications into health care.

Start Simple and Meet End Users' Needs

For health care organizations interested in developing or implementing genAI solutions, it is important to start simple (e.g., small tests of change) and to ensure that applications meet end users' needs and are in the best interests of ensuring patient safety, including streamlined integration into the daily workflow and experience of patients and the health care workforce.

Questions to consider:

- What problems do clinicians and staff want solved?
- Is there a genAI solution to meet this need that offers objective evidence of safety and effectiveness?
- Is an AI application feasible for our setting and is there a relevant use case?
- How will this AI application impact the safety, experience, and outcomes of patients?
- Have we assessed the potential reward and risk related to this potential AI solution? If not, how will be assess for reward and risk (e.g., a failure mode and effects analysis, if applicable)?

Organizations also need to ensure that any genAI application considered for implementation has been rigorously validated, tested, and piloted prior to scaling, including small tests of change, and that the proper processes are in place to monitor the application's performance on a consistent basis. For example, one organization engaged in our research shared that their AI oversight committee reviews data and algorithm performance every six months to ensure high-quality performance. Health systems must remember that AI technology is not simply plug-and-play, but instead requires ongoing monitoring to ensure performance quality and identify opportunities for improvement.

Moreover, how organizations communicate with staff and disseminate information on organizational genAI efforts is critical to implementation success. Clinicians and staff may have concerns about loss of autonomy in their role, staff reductions, and job loss with the introduction of AI applications.[90] Because of this, health system executives and governance members need to reassure staff that AI applications are complementary tools that must be supplemented with clinical judgment provided by humans.[91] As the literature notes, the implementation of AI tools aims to improve the patient experience and improve clinical safety and reliability as well as allow clinicians to upskill and practice at the top of their license.[92,93] Likewise, organizations must not underestimate the importance of change management when introducing AI tools to support workflows and clinical care delivery.

Risk Identification, Mitigation, and Monitoring

Experts encourage health care organizations to develop or expand the needed governance and oversight bodies to support AI implementation in two fundamental ways.

- Identify and mitigate risks and unintended consequences associated with AI tools.
- Develop a cohesive and transparent organizational approach to AI that includes:
  - Education and training;
  - Guardrails to ensure safe use;
  - Processes for design, implementation, and monitoring; and
  - Mechanisms for collaborative learning within the organization and broader health care sector.

Collaboration and the need for learning health systems were consistently highlighted by experts as an important consideration for AI's integration into health care. Although data, algorithms, and applications are often proprietary to AI vendors, siloed efforts may not only stymie technological advances to improve care, but could also obscure repeated and preventable adverse events. Sharing experiential learning from design and implementation efforts across health care systems and the industry could help mitigate potential harm and bolster monitoring efforts to ensure that genAI is applied safely. Further, collaboration may help prevent variation. As one expert noted from their experience with new technologies, variation can lead to a lack of interoperability and complicate the landscape, opening the door for errors to occur.

For internal mitigation strategies, experts suggested the development of audit tools, including, but not limited to, algorithmic auditing, use of patient and clinician user feedback and rating of AI-generated results, and ongoing independent testing with validation sets. They cited the need for establishing accepted limits to the technology prior to implementation, such as hard end points (e.g., mortality), performance metrics, and accepted error rates for technology, if any.

This IHI Innovation Report identifies two main perspectives on potential harms arising from use of genAI tools in health care.

- The first perspective highlights the upsides of genAI tools and regards the downsides as addressable and/or not qualitatively different from existing problems in health care without AI. For instance, chatbots may at times produce medical notes with factually incorrect information (i.e., hallucinations or confabulations) and many clinicians may skip checking and correcting such inaccuracies. Some ask whether and how this differs from traditional dictated notes that often contain incorrect transcriptions and other errors that remain uncorrected in the medical record, which may then be copied and pasted as inaccurate notations without review. The optimistic perspective also points out that with use of AI tools, on balance, we might come out ahead with improvements in patient and workforce safety and well-being.

- The second perspective takes a more skeptical view on whether the promise of AI will materialize to provide benefit for the quality and safety of care and caring. After all, EHRs were also supposed to make clinicians' lives easier. Yet, a noted advantage in favor of AI is that it can address clinician burnout attributed to EHRs. This uncertain and critical stance toward AI in health care also worries about the pace at which massive and potentially irreversible changes may be instated in health care. These changes impact how clinicians and patients interact, displace the human workforce, and open the door for enormous privacy breaches, the commercialization of private health care information, and long-lasting implications of care delivery and clinical practice patterns.[94] As noted at the outset of this report, health care is posed to adopt AI tools at the same time that computer science experts, including some of the researchers who pioneered the development of these tools, have called for a pause on further AI tool development to allow time to establish regulations and other safeguards to protect society from potential risks from the technology.[95,96]

Given both the promise and apprehension surrounding AI-related developments in health care, organizations seeking to explore genAI tool integration are strongly encouraged to consider the recommendations that follow.

- **Be cautious and critical.**

  Health care systems and workers must be steadfast in their dedication to patient safety, quality care, and evidence-based practices. There are many risks detailed throughout the report (and in Appendix A) that emphasize the importance of a thoughtful and vigilant approach to AI integration in health care. While AI can relieve existing burdens within health care, its integration needs to be based on rigorous evaluation and peer-reviewed evidence.

- **Be strategic and collaborative.**

  The design, implementation, and use of genAI should be strategically constructed to align with existing organizational goals or roadmaps, meet workforce needs, fit into existing workflows, and safely support clinical care delivery. Health care systems must ensure that AI tools and applications are not prioritized over workforce and patient well-being and safety.

  As with any major new technology or process change, organizations will need to develop teams to govern, plan, and support the design, implementation, and monitoring of AI tools, with representation from different health professions (e.g., physicians and nurses), clinical informaticists, quality and safety personnel, and patients and families, among others. Stakeholder diversity is important to ensure that applications are designed and implemented to continually meet end users' needs and mitigate risks for safety and equity. Once a team or teams are established, it is important for organizations to develop standard processes for considering, designing, and/or implementing AI solutions as well as guardrails or standard practices for the professional use of AI. It is likely that these processes and guardrails will change as rapidly as the AI landscape in health care, but it necessary to ensure that structures are in place to regulate the design, implementation, and use of AI for the safety of the patients, the workforce, and the health care system.

  Further collaboration is encouraged between health care systems, academic institutions, technology companies, and others to ensure that genAI tools and applications are used safely and ethically and to pursue opportunities to improve the quality of care with AI assistance. This collaboration can also help establish industry standards, practices, and guidelines.

- **Be prepared and intentional.**

  It is important for health care systems to appropriately prepare for AI integration. This includes developing robust governance and oversight bodies (including considerations for evaluation and monitoring), educating the workforce (e.g., how AI works, appropriate use and risks of AI tools), and evaluating organizational infrastructure to ensure that a health care system can safely support the technological or computational demands of potential AI tools and related infrastructure needs. Taking the time and resources to prepare a health care system for AI integration demonstrates an intentional and proactive approach to this emerging technology, which can help mitigate potential risks or unintended consequences of integration.

Conclusion

The emergence of genAI has reignited widespread interest in and enthusiasm for implementing AI tools in health care. Yet, this enthusiasm should not distract us from identifying and addressing serious potential harms.

The genAI applications health care organizations are most likely to see implemented now or in the immediate future include documentation support and chatbots to help answer questions from patients. Given the fast-paced and dynamic nature of AI in health care in addition to the tension of the perspectives detailed above, this report does not offer any specific recommendations on how to design, implement, or regulate this technology. Rather, we stress the need for further research and evaluation to assess the quality and safety of emerging AI technologies to ensure maintenance (and even improvement) of clinical care delivery and workforce well-being.

AI in health care is a promising but complex field. As such, it requires careful consideration of ethical, legal, social, and technical issues. We strongly encourage organizations to consider building systems to support AI application design and implementation in a safe manner by building governance structures, using caution when designing, evaluating, implementing, and monitoring AI, and starting simple with small tests of change that meet end users' needs.

Appendix A: Risks, Challenges, and Unintended Consequences of Generative AI Clinical Applications in Health Care

Table 4. Risks, Challenges, and Unintended Consequences of Generative AI Clinical Applications in Health Care (listed alphabetically by category of concern)

Data Concerns	
Biased, inaccurate, aged, or inappropriate training data	Models rely heavily on their training datasets to learn how to function. Yet, datasets provided to models or algorithms may codify existing human biases or simply not include enough data involving underserved populations, resulting in inaccurate or misleading outputs. For instance, one study demonstrated higher false negative rates (i.e., missing signs of disease) in AI-interpreted radiographs involving racialized patients.[97]
Falsehood mimicry	Occurs when the user inputs a factually incorrect prompt, leading to the generative AI tool producing an erroneous output instead of first asking clarifying questions that might lead to factual correction.[98]
Hallucinations or confabulations	False or made-up statements presented as factual. "Content that is nonsensical or untruthful in relation to certain sources."[99] While hallucinations remains the commonly encountered term, confabulations is the better term for logical sounding, semantically coherent statements not based on distorted or mistaken sensory input.[100,101]
Erosion of human oversight (preserving a "human in the loop")	Implementing AI algorithms and tools without human supervision creates the potential for risk. Maintaining a "human in the loop" can help ensure that AI tools are functioning properly with reliable and accurate outputs and meeting users' needs.
Lack of AI transparency and explainability (the "black box")	AI algorithms and models are often unable to disclose how outputs (or results) are reached, hence the term "black box." This lack of transparency and explainability may lead to skepticism or mistrust among clinicians and patients.[102]
Poor quality, inaccurate, or biased data and limited data quantity	Existing data that AI tools process, such as EHR data, may be inconsistent, incomplete, missing, or incompatible. Thus, the AI output may be unreliable due to the quality of the data input (e.g., visit notes, discharge summaries).[103,104] This can also include the exclusion of relevant data (e.g., failure to incorporate variables to improve outcome accuracy). Further, available data quantity may be limited for training, testing, and auditing purposes, which may decrease the effectiveness of an AI algorithm.

Ethical Concerns	
Increase inequities related to design and access to quality AI solutions	AI technology is a double-edged sword for health equity. To improve health equity, AI can transform decision-making and medical treatment, particularly in primary and preventive care, as well as support patient-centered care.[105] The technology can also support marginalized and underserved communities such as rural communities and non-dominant language speakers.[106,107] However, AI-related barriers to health equity include codified algorithmic or dataset bias (including training and validation), inequitable accessibility or affordability of AI tools, and practice bias (e.g., clinician bias in using AI tools or interpreting/applying AI outputs, underperformance in certain groups).[108] This, in combination with concerns about cost, could further drive inequities between health care systems and their ability to deliver quality care, and patients' ability to access and afford quality care.
Limited guidance on standard operating practices and regulations	At the time of publication, standard practices and regulations such as SaMD that are relevant to AI applications in US health care remain unestablished. Moreover, some experts caution against relying on HIPAA compliance as fulfilling the duty to maintain patient confidentiality.[109]
Prioritization of commercial interests	A handful of experts noted that technology companies were pushing them to move faster than they were comfortable with, and that the Silicon Valley paradigm does not apply to health care ("move fast and break things").[110] With many health care systems partnering with technology companies and corporations, it is critical that health care prioritize patient well-being and safety. This also acknowledges that prioritization of commercial interests, including those of health care systems, could inhibit efforts to collaborate on AI application design and implementation across health care systems and across industries.
Public trust	Credibility is important for AI to be successfully integrated in health care.[111] The public, including the workforce and patients, must trust the AI tools and clinical use of the tools. Losing public trust is risky as second chances are unlikely should AI cause harm in health care ("user and regulator trust are easy to lose and very hard to regain").[112] Clinician uptake of AI applications for care delivery will rely on successful and evidence-based demonstrations that the tools are safe.[113]
"Shiny object" syndrome	AI and genAI have captured attention, but the hype should not be overstated. While this may be a worthwhile new pursuit, health care systems must note the risks involved in what could be a distraction or "shiny object."
Managerial and Operational Concerns	
Cost	While genAI solutions in health care may save health care systems money, the upfront investment may not be feasible for some organizations, including under-resourced systems.[114] This could have implications for equitable access to quality health care.

Data privacy, protection, and security	Health care data is sensitive and personal and must be protected from unauthorized or inappropriate access, theft, or misuse. AI introduces new data and infrastructural demands, raising concerns about how health care can use this advanced technology while ensuring that data is protected and secure. Risks to consider include unauthorized access, use, and control of patient data by private entities, as well as external threats (e.g., threat actors) of data breaches or leaks.[115] Additionally, patients need to be confident that their data, if they consent to share it, is being used ethically and securely.[116]
Data storage and the cloud	Health care data storage capabilities must keep up with the data demands of advanced technology such as AI. Because of this, questions emerge on whether on-site data storage is still viable or whether cloud storage should be invested in. Yet, multiple risks arise with the move to the cloud, including existing organizational policy for on-site storage of health care data, data ownership and user agreements with third parties, and patient privacy and consent to storage. Further, the cloud may not offer adequate safeguards for data encryption, backup, or recovery. Experts provided mixed responses on whether moving health care data to the cloud posed an increased risk to data security.
Liability for health care systems and clinicians	GenAI is a grey area for legal matters in health care, particularly liability. Legal liability for a health care system or clinician could include cases of data breaches, intellectual property rights, and patient consent and comprehension (e.g., if a patient does not comprehend the implications of their agreement).[117,118] Further, malpractice could cause public mistrust of new technological advances and necessitate new regulations and licensing.
Lack of interoperability	Lack of interoperability is applicable to both data and infrastructure. First, data may not be compatible or standardized across different systems or platforms. Second, with multiple applications and vendor options (as well as internal design and implementation), there is increased variation in AI application design and functionality, which may not be compatible with other applications or existing hardware and software in use in a health care system.
Lack of strategic planning	The successful design, implementation, and continued use of new technology such as AI relies on careful planning by leadership. "AI initiatives often fail because they are implemented as standalone projects. To ensure the success of AI efforts, AI must be integrated into the strategic planning process so that it aligns with the goals and objectives of the organization."[119] Without proper strategic planning, organizations risk poor outcomes, including low clinical use or uptake and poor workflow integration, which could dampen future efforts to introduce AI applications.

Limited existing infrastructure	AI applications can require a significant amount of computational power to run. Because of this, health care systems may create risk if they implement AI without the proper IT infrastructure in place. Lack of supporting infrastructure could lead to delays in clinical care or gaps in accessing technological advances to improve care.
Poor governance and oversight	Inadequate governance or oversight of emerging technologies such as genAI could increase the potential for other risks listed in this table to translate into real-world harm, including ethical concerns on privacy, trust, and bias as well as regulatory concerns.[120]
Potential for downtime	All technology can malfunction and must be maintained and updated. As genAI solutions are integrated, systems must consider the risk for planned and unplanned downtime to ensure continuity of care.
Patient and Workforce Concerns	
Alert fatigue	Refers to the desensitization of clinicians to safety alerts, which causes clinicians to ignore or fail to appropriately respond to warning systems.[121]
Automation bias, overreliance, clinical complacency, and deskilling	These terms collectively refer to the possibility that the use of genAI tools in health care will lead to a decrease in workforce competency. Overreliance "... occurs when users excessively trust and depend on the model, potentially leading to unnoticed mistakes and inadequate oversight."[122] This can lead to automation bias, which is "the tendency to over-rely on automation."[123] Clinical complacency and deskilling, then, can occur as clinicians may no longer employ or improve their skills.[124] This can lead to a loss of skills, inability to reliably detect mistakes or errors, and reduction in decision-making quality, diagnostic reasoning, and patient communication.
Difficulty integrating into daily clinical workflow	For genAI tools and applications to be successful, they must integrate into existing clinical workflows. An evidence-based and clinically tested genAI tool will be underutilized if it is inconvenient to a clinician or staff member's daily workflow. Risks include improper use or underutilization of tools that could improve care delivery and patient outcomes.
Fear that care will be depersonalized	Refers to the concern that the implementation of AI in clinical care settings will negatively impact the patient-clinician dynamic. This includes the possibility that clinicians may prioritize the clinician-technology relationship over the patient.
Lack of patient education on AI	The general patient population may be unfamiliar with the use of genAI tools and applications in health care. Health care systems and clinicians must ensure that patients are aware of the uses and risks of genAI tools as well as their patient rights, including those pertaining to patient data. Further, clinicians need to be aware that, even though patients may lack education on AI, they may be using it in their daily lives, including asking applications like ChatGPT for medical advice.

Lack of proactive safety oversight and engagement of related expertise	Implementing AI requires engaging multiple stakeholders, including for planning, evaluation, and decision-making. The need for multiple stakeholders can be challenging, but the process should not advance without adequate resources and expertise from safety, quality, and risk teams. Further, use a proactive safety approach through design and integration along with appropriate expertise.
Misalignment with patient preference	Patients may prefer not to receive clinical care assisted by genAI tools. In 2023, Pew Research found that 60% of surveyed Americans were uncomfortable with their health care provider using AI.[125] Health care systems must consider how to handle patients who opt out of AI tools, and adequately educate patients on AI tool use for those who opt in.
Workforce resistance	With the introduction of genAI tools and applications, the health care workforce may be resistant to this integration for multiple reasons, including fear of replacement and workforce displacement.[126,127] Resistance by the workforce could reduce the likelihood of successful implementation of tools aimed at improving care quality and workplace environment and workload.

Appendix B: Non-Clinical Applications of Generative AI in Health Care

More detailed information for each genAI application follows Table 5.

Table 5. Overview of Non-Clinical Generative AI Applications in Health Care

GenAI Application	Potential Benefits	Considerations
Publications	• Assist with literature reviews • Create or edit written drafts	• Intellectual property rights • Authorship • Hallucinations and confabulations such as with content and references
Clinical trials and medical research	• Generate and synthesize data • Propose clinical trial design • Offer outcome predictions • Detect the likelihood of adverse effects or events • Streamline and improve appropriateness of clinical trial recruitment	• Regulatory compliance • Overreliance
Education for medical and other health care students Education for patients	• Produce medical simulations or narrative cases for medical students • Provide an assessment tool for medical students • Provide patient education about their condition(s), medication(s), and treatment plan • Support health literacy for the general population	• Ensuring appropriate use • Plagiarism • Falsehood mimicry (see Appendix A) • Hallucinations and confabulations • Language and health literacy
IT support	• Provide middleware to support interoperability of existing platforms and systems • Predict maintenance for technology	• Potential for downtime • Aged datasets
Administrative assistance	• Streamline appointment scheduling • Act as a digital assistant	• Potential for downtime
Medical billing, coding, and claims	• Automate the process of coding medical procedures and services • Identify and correct coding errors • Optimize revenue and ensure compliance • Draft documentation for pre-authorization, claims, reimbursements, and appeals	• Poor data quality (or need for data fidelity) • Denial of legitimate claims • Increased clinician time to challenge denials

Safety and quality improvement practices	• Provide data analysis, data visualization, process analysis, qualitative analysis, and guidance for developing and testing changes	• Safety, accuracy, and reliability of LLMs in health care • Data concerns (e.g., biased, inaccurate, out-of-date, or inappropriate training) • Hallucinations • Data privacy and security concerns • Liability or copyright implications • Workforce displacement • Environmental impact (e.g., high greenhouse gas emissions due to demand of computing power and enormous use of water for cooling data centers)

Publications

GenAI has the demonstrated ability to assist with research and writing and may be useful for clinical publications. The technology could be used to support medical writing (including peer-reviewed publications and practice standards), assisting with literature reviews, and editing human-written drafts or providing written drafts for humans to edit.[128,129]

Concerns about this usage have been raised, including intellectual property rights, authorship, hallucinations, and confabulations, including fabricating nonexistent references. Because of this, journals such as *JAMA* have published guidance for authors, peer reviewers, and editors on the use of these technologies, including AI, LLM, and chatbots.[130]

Clinical Trials and Medical Research

GenAI could reshape clinical trials and medical research processes by accelerating timelines and enhancing outcomes, especially for drug discovery and development. Using historical clinical trial data and established trial parameters (e.g., desired outcomes), genAI could support clinical trials by:

- Generating and synthesizing data;
- Proposing clinical trial design;
- Offering outcome predictions;
- Detecting the likelihood of adverse effects or events; and
- Streamlining trial recruitment and targeting potential enrollment opportunities based on predefined criteria.

Yet, the use of genAI in this capacity is untested and must be rigorously evaluated and validated prior to implementation. If utilized, applications need to comply with regulatory requirements, including HIPAA, existing or pending Food and Drug Administration regulations, and other national or international standards and regulations. Further, even with genAI support, clinical researchers cannot become complacent or overreliant on technological assistance; a human must always be in the loop if technological applications are used.

Education for Medical and Other Health Care Students

GenAI could enrich educational opportunities for medical students. As an experiential tool, genAI can be used to produce medical simulations or narrative cases for medical students, which could be offered on demand, to work through to test and enhance their critical thinking and clinical reasoning.[131] Although untested as an assessment tool, genAI, specifically ChatGPT, has demonstrated the ability to comprehend and respond to standardized tests in higher education. For example, one study found that ChatGPT performed above the 60 percent threshold on the United States Medical Licensing Examination Step 1 (using publicly available sample questions).[132] While only theoretical, it is possible that genAI could be used as an assessment tool for medical students, in conjunction with human proctors to ensure that questions and responses are accurately communicated. This function may also assist with producing appropriate questions for standardized tests and could be used for continuing education for health care professionals.

Implications for genAI in education include ensuring appropriate use by faculty and students, concerns about plagiarism (including inadvertent cases), and application issues such as false mimicry, hallucinations, and confabulations. Many universities have made an effort to provide guidance for the use of genAI both for students and faculty, including Harvard University, the University of North Carolina–Chapel Hill, and Tufts University.[133,134,135]

Education for Patients

GenAI could provide patients with education on their conditions or illnesses, medications, and treatment plans. GenAI applications, like ChatGPT, have the capacity to provide patient education. For example, a group of physicians assessed ChatGPT on its knowledge of colonoscopies and found that it provided adequate and original responses to frequently asked questions about the procedure. Further, some companies have taken strides to support patient education, such as Vital's AI-powered video education feature that auto-prescribes education to patients in the emergency department and inpatient settings.[136,137]

IT Support

GenAI may support two functions for health care IT:

- GenAI applications may be capable of providing middleware to support interoperability between systems and platforms.
- These applications can provide predictive maintenance for technology.[138]

Beyond routine maintenance, genAI can be used to anticipate machine malfunctions and to plan maintenance prior to errors occurring, which could decrease delay and replacement costs. Even with technological support for IT maintenance and predictive malfunction, manual maintenance must still be routine, including maintenance and auditing of any genAI supporting health care IT.

Administrative Assistance

There are several potential benefits of genAI for health care administration:

- GenAI can optimize scheduling processes for health care services.[139] GenAI applications can automate the tasks of scheduling appointments, centralizing scheduling across multiple locations and departments, managing call centers, balancing workload among staff members, and forecasting appointment demand.[140]
- GenAI can enhance the role of digital assistants in health care settings by enabling digital assistants to perform diverse functions, such as reviewing daily schedules, evaluating appropriateness of visit type, answering queries, providing guidance, collecting feedback, and generating reports.

Downtime options and backup procedures must remain available in case of emergencies or routine maintenance interruptions. Staff using genAI for scheduling or related responsibilities need to be trained appropriately, both in manual and genAI supported methods, to ensure efficient and safe use of AI tools for patients and to increase workforce satisfaction with supplemental support. In all cases, the use of AI should be closely monitored to ensure that users do not become overly reliant on digital assistance.

Medical Billing, Coding, and Claims

GenAI can streamline billing, coding, and claims for health care systems. Generative AI can help automate the process of coding medical procedures and services, identify and correct coding errors, optimize revenue and ensure compliance, and draft documentation pertaining to pre-authorizations, claims, reimbursements, and appeals.[141,142] If genAI is used for medical billing, coding, and claims, it is important to ensure data fidelity prior to implementation, otherwise the application may struggle to output accurate information. Even if data fidelity is established, an appropriately trained human needs to remain in the loop and the AI algorithms and data need regular auditing. Established risks to these applications include the inability of AI to make informed, evidence-based decisions, and the high level of denials of prior authorizations has created extensive challenges, leading to patient harm and excessive burden and costs for clinicians to advocate for appropriate care.[143]

Safety and Quality Improvement Practices

Safety and quality improvement efforts in health care may benefit from genAI tools and applications, including data analysis, data visualization, process analysis, qualitative analysis, and guidance for developing and testing changes. These uses can support the maintenance and improvement of the quality and safety of clinical care delivery. Notable challenges and risks include concerns on the safety, accuracy, and reliability of LLMs in health care; data concerns (e.g., biased, inappropriate training data, out-of-date data); hallucinations; data privacy and security concerns; liability or copyright implications; workforce displacement; and environmental impact (e.g., high greenhouse gas emissions due to demand of computing power and enormous use of water for cooling data centers).

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HEALTH

THE MAKING OF A DIAGNOSTIC MIND

"To me, the concept of the master diagnostician is that you're never good enough," one doctor said.

By Alexandra Sifferlin

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Illustration by Ada Zejun Shen

MARCH 31, 2026 SHARE AS GIFT DISCUSS 30 SAVE

Gurpreet Dhaliwal sat onstage in a hotel ballroom in Minneapolis. The gray curtains behind him were illuminated by bright blue lights, giving the slightest hint of performance at an otherwise typical medical conference. The presentation was among the most anticipated at the Society to Improve Diagnosis in Medicine's 2022 meeting. The attendees were there to watch a kind of showcase: a complex diagnosis in action.

Dhaliwal, a professor of medicine 30 sco, was given the details of a patient he had never seen before. As another physician slowly revealed pieces of the case, Dhaliwal narrated his thinking out loud: why he was considering one possibility and rejecting another, and what each new clue revealed for him. Eventually, he decided that the patient was likely suffering from a dangerous buildup of pressure in her abdomen. Left untreated, she could experience organ failure. It was the correct diagnosis, and the audience responded with applause.

Dhaliwal is regarded as one of the country's most gifted diagnosticians. Colleagues have praised not only his command of physiology but also his ability to make his reasoning legible—to turn clinical uncertainty into something teachable. "To observe him at work is like watching Steven Spielberg tackle a script or Rory McIlroy a golf course," a *New York Times* reporter wrote in 2012.

"I appreciate the designation but sort of reject it, only because of my own philosophical stance, which is that it's very hard to master the diagnostic process," Dhaliwal told me when I talked with him for my book about diagnosis. He considers himself a student of diagnosis, committed to getting better. "To me, the concept of the master diagnostician is that you're never good enough."

That belief puts Dhaliwal on one side of a core question of medicine: Are some doctors inherently better diagnosti 30 or is diagnostic excellence a skill that any clinician can achieve? Doc t right—some estimates suggest about 90 percent of the time. But with roughly 1 billion physician-office visits each year in America, even a low error rate can still affect a large number of people. A 2023 study estimated that 371,000 people die a year and 424,000 are disabled following a misdiagnosis.

In 2015, the National Academies of Sciences, Engineering, and Medicine published a seminal report on diagnostic error with a startling finding: Most people will experience at least one (such as a delayed, wrong, or missed diagnosis) in their lifetime, "sometimes with devastating consequences." That report prompted a small but vocal group of physicians and other health providers to look inward. They argue that the number of diagnostic errors is unacceptable and must be improved. Dhaliwal has been part of the movement to figure out how.

Some research suggests that many, if not most, diagnostic errors arise from failures in thinking—cognitive bias, premature closure, insufficient reflection. Accordingly, some researchers frame diagnostic error as largely a problem in clinical judgment: the ability to reason through uncertainty and weigh competing explanations in order to reach the right diagnosis and make decisions about care. "Regrettably, how to think in medicine has been a much-neglected area for medical educators, who stalled somewhere in the Middle Ages, or a century or two earlier," Pat Croskerry, a retired professor in emergency medicine at Dalhousie University in Canada who's known for his work on cognitive errors in the diagnosis, told me.

Dhaliwal credits his own abilities to paying close attention to his own thinking. "I do think you can train yourself to be a better diagnostician," he said. Early in his training, he closely observed the physicians he most admired. Some of them had a knack for identifying rare diseases that evaded their peers. Others mastered the diagnosis of common conditions so thoroughly that they could recognize every permutation of pneumonia. Dhaliwal wanted to excel at both.

But when he asked physicians how kind of doctor, their advice was usually the same: *See a lot. Read a lo* ying. Every physician sees patients. Every physician reads. What, he wondered, truly separates an exceptional diagnostician from a competent one?

He hung on to this question, and about two years after finishing residency in 2003, during a yearlong faculty-development course for medical educators, he encountered a session on clinical reasoning—an emerging field at the time. The physician and medical historian Adam Rodman has described clinical reasoning as "the study of the ability for expert physicians to see what others don't." Researchers were beginning to investigate what actually happens in doctors' minds when they make diagnoses: how they organize their knowledge and put it into practice. Dhaliwal quickly recognized this as the quality he had seen in his role models, even though "they didn't have a term for it, and neither did I." The idea of *clinical reasoning* helped clarify the process; the next question was how to get better at it.

Dhaliwal laid out the key steps of a doctor's reasoning process: collecting data from a patient; synthesizing that information; accessing "files" in the mind, including the details about diseases and how they present; listing possible diagnoses; and choosing one over others. He also began studying the science of expertise and how people—whether Nobel laureates, Olympic swimmers, or mechanics—become exceptional in their field. "They seek out challenges, whereas most of us instinctively try to minimize challenges after we're competent," he said.

They also learn from their mistakes. In a 2017 paper, Dhaliwal wrote that ordinary people develop "extraordinary judgment by extracting as much wisdom as possible from their inevitable errors," a lesson he drew from Philip Tetlock and Dan Gardner's book, *Superforecasting: The Art and Science of Prediction*. But medicine doesn't make that easy for doctors, who may treat a patient once and never see them again. If the patient's condition worsens, or they receive a different diagnosis later on from someone else, that information may never make its way back to the first doctor. With these ideas in mind, Dhaliwal set out to sharpen his skills. Today, he works in the San Francisco VA Medical Center's emergency room, where he sees a variety of illnesses and necessarily follows that early ad[...] of patients. But, crucially, he also started keeping track of his own ca[...]uld follow up on what happened.

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When he discovers he was wrong, he tries to figure out why. Did he miss something important? Was he exhausted at the end of a long shift? Did he anchor himself to a particular conclusion too quickly?

"I started to get kind of addicted to it," he said. He explained that the mind wants closure; without knowing the outcome, people tend to assume that things turned out well. His habit of tracking down a patient's outcome echoes advice delivered more than a century ago by William Osler, one of modern medicine's founding figures: "Learn to play the game fair, no self-deception, no shrinking from the truth; mercy and consideration for the other man, but none for yourself, upon whom you have to keep an incessant watch." Diagnostic mastery, Dhaliwal illustrates, is not a mysterious gift bestowed on a talented few. It is the result of examining one's own thinking and practice without mercy.

But the reasoning that goes into diagnosis may start to look very different. Since his third year of medical school, Dhaliwal has read *The New England Journal of Medicine*'s Clinicopathological Conference, or CPC. The CPC is a teaching exercise in which doctors are presented with a real patient's case and asked to reason aloud toward a diagnosis, similar to Dhaliwal's Minneapolis presentation. Last fall, Dhaliwal participated in a CPC that put him in competition with an AI agent called Dr. CaBot, a medical-education tool developed by researchers at Harvard Medical School.

Both Dhaliwal and Dr. CaBot reached the correct diagnosis and explained their reasoning step by step. They correctly concluded that the patient had a problem in the upper part of his digestive system, which caused a bacterial infection to trigger sepsis, among other complications. Dr. CaBot didn't identify the cause of the problem, whereas Dhaliwal deduced, correctly, that the man had swallowed a toothpick, which poked through his gut and caused the infection. He had seen that kind of case before.

That Dr. CaBot's problem-solving c[illegible] it did to Dhaliwal's is both promising and disconcerting: It su[illegible]nes may be able to match the

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performance of elite diagnosticians. More formal evidence also indicates that large language models may be able to approximate the kind of clinical reasoning expected of physicians. One study published in July 2024 found that when OpenAI's GPT-4 examined the medical information of 100 patients in an emergency room, the AI was able to diagnose them with 97 percent accuracy, outperforming resident physicians. (OpenAI's models have advanced since then.) Another study found that ChatGPT scored higher on a clinical-reasoning measure than internal-medicine residents and attending physicians at two academic medical centers. Other studies have been more mixed.

Serious concerns about reliability, sycophancy, and hallucinations remain. But in some ways, what a diagnostician does is not so different from what AI claims to do. Both use enormous amounts of information to recognize patterns in symptoms and diagnoses that tend to appear together. A doctor does this through medical education and personal experience; AI does it by predicting plausible explanations based on statistical patterns it has learned from its training materials.

"This is an electric moment in medicine," Mark Graber, a physician and co-founder of the nonprofit Community Improving Diagnosis in Medicine, told me. "If you can come up with an AI agent that's as good as Gurpreet Dhaliwal, that is an amazing accomplishment that will surpass the abilities of 99.9 percent of doctors."

How medicine embraces any of this is an open question. Perhaps AI will strengthen clinicians' reasoning and close the gap between the Dhaliwals and everyone else. Or it could become a crutch for clinicians, and lead them to lose skills. A 2025 study found that after just three months of using an AI tool to find precancerous growths during colonoscopies, doctors were less likely to identify the growths on their own.

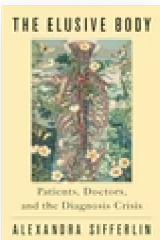
For his part, Dhaliwal is equanimous. "I think AI is going to transform health care radically. I don't think it's going to change doctoring radically," he said. He believes that AI is likely to perform best at the extremes of diagnosis: the very simple cases (such as a poison-ivy rash) and the [illegible] 30 [illegible]es (rare or novel diseases). In the not-so-distant future, people may be able to get answers to routine medical questions at home—*What's this spot? Is my cough concerning? How's my blood pressure?*—without ever needing to see a physician. That may be entirely appropriate, because attending to these everyday concerns usually does not require sophisticated clinical judgment or nuanced decision making.

AI could also prove valuable in identifying conditions that a physician may never encounter in their career, or in helping diagnose patients that have stumped multiple clinicians. These cases tend to hinge on how encyclopedic a doctor's knowledge of the medical literature is; AI can recognize obscure patterns across millions of cases and publications, and surface possibilities that may lie outside any single physician's experience.

"What I think is less likely to change is sort of the muddy middle, which is what I think the vast majority of medical practice is," Dhaliwal said. Much of medicine involves choosing between possibilities: Does a person have an infection, an allergic reaction, or an autoimmune disease? Is it a psychiatric or medical issue? AI could certainly help parse through the options. But medical judgment goes beyond identifying what's most likely; it involves deciding what the diagnosis means for a particular patient. Two people diagnosed with the same cancer may desire different futures. One may want the most aggressive treatment available, whereas the other may decline interventions that would trade quality of life for longevity. These are value-laden decisions that, at least for now, still require something irreducibly human to navigate. An LLM can recite treatment options and survival rates, but it cannot share responsibility for the choices that follow.

Relying on AI for certain aspects of diagnosis could help free doctors to focus on those more human parts of the job. In the United States, more than 100 million people don't have a primary-care provider, and the profession itself is dwindling. "If in some form AI is able to beat us, or help us improve our ability to do clinical reasoning, you don't have to be the smartest person in the room to be a physician, which I think is better for the community," Jeffrey Goddard, a medical student at the University of Iowa who uses chatb 30 , told me. A diagnosis, most simply, is an answer to the question *What is making me ill?* But it can offer much more than that—reassurance, coherence, and, ultimately, relief. Not all of that can be outsourced.

This essay was adapted from Alexandra Sifferlin's book, *The Elusive Body: Patients, Doctors, and the Diagnosis Crisis,* published today.



The Elusive Body - Patients, Doctors, And The Diagnosis Crisis

By Alexandra Sifferlin

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REVIEW

Artificial Intelligence in Healthcare: A Narrative Review of Recent Clinical Applications, Implementation Strategies, and Challenges

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Abstract: Clinical documentation demands are increasingly eroding clinician time and morale. Large language models (LLMs) are emerging as practical allies, drafting notes in real-time and laying the groundwork for decision support. This narrative review examines both recent clinical applications of AI across healthcare domains and leadership strategies for implementing these technologies in hospitals and ambulatory networks. We conducted a narrative review of recent literature and high-quality practice reports published, focusing on leadership strategies for implementing LLMs in hospitals and ambulatory networks. Evidence shows that when executives establish multidisciplinary AI committees, run quickly iterated pilots, and embed continuous bias and safety audits, LLM deployments improve workflow efficiency and clinician satisfaction without compromising quality. Effective programs pair clear vendor scorecards with transparent communication to staff and patients and align metrics with broader equity goals. Recent regulatory frameworks in North America and Europe reinforce the need for life-cycle governance and performance monitoring. The review concludes with a leadership roadmap linking strategic vision to practical actions that sustain safe, equitable, and financially sound LLM integration.

Keywords: AI in healthcare, healthcare AI, LLMs in medicine, clinical decision support AI, healthcare leadership and artificial intelligence

Introduction

Current projections estimate the healthcare artificial intelligence (AI) market will expand from USD 26.6 billion in 2024 to USD 187.7 billion by 2030. This growth correlates with widespread integration, as approximately 80% of organizations now utilize AI applications.[1] The driving force behind this growth is the massive volume of medical data generated from electronic health records and imaging scans to genomic tests and continuous monitoring. Modern research suggests that only about 30% of health outcomes are determined by genetics, while roughly 60% come from lifestyle and environmental factors, highlighting how much information resides outside the clinic that AI could analyze. By finding subtle patterns across these data sources, AI promises "unprecedented opportunities" to assist clinicians and reduce errors.[2]

This transformative potential has spurred the rapid adoption of AI in healthcare. Industry surveys demonstrate that 66% of US physicians now use AI tools in their practice (up from 38% just a year earlier).[3] These tools range from image analysis software to predictive models that sift through patient records. During the COVID-19 pandemic, AI models were hastily developed to detect infections on chest scans or to predict patient deterioration,[1] demonstrating how rapid

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innovation could yield clinically useful tools. Consistent with these trends, the American Medical Association emphasizes that AI must be employed as "augmented intelligence," a support for clinicians, not a replacement for human judgment.[3] However, a critical barrier to realizing these benefits at scale is the gap between AI's technical capabilities and its successful real-world implementation, which includes clinical validation, workflow integration, equity assurance, and sustainable governance.

At the same time, deploying AI in healthcare faces significant challenges. Medical data is sensitive and often siloed across institutions, so building reliable models requires careful data engineering and privacy safeguards.[2] Patient confidentiality must be protected: techniques like federated learning (training AI across multiple sites without sharing raw data) are being developed to allow large-scale AI learning while preserving privacy.[2] Regulators and professional societies are also trying to keep pace. For example, the US FDA has issued draft guidance for AI-driven medical software (often called "Software as a Medical Device"), and medical societies are working on ethical frameworks and best practices for clinical AI. Overcoming these hurdles is an active process.[4]

We employed a narrative review methodology to synthesize both emerging clinical evidence and practical implementation frameworks across diverse AI applications. This approach allows for broader inclusion of recent case reports, expert guidance, and real-world deployment experiences that offer practical advice for healthcare leaders navigating rapid technological change.

To bridge the implementation gap, this review examines areas where AI is making a difference in healthcare today and provides evidence-based strategies for healthcare leaders to deploy these technologies safely and equitably. The sections below discuss major clinical domains, imaging diagnostics, patient monitoring, surgical care, and health system management, showing how AI can improve efficiency, accuracy, and patient outcomes. These sections also discuss illustrative case examples and remaining ethical and practical challenges to provide an in-depth look at AI's role in healthcare. As depicted in Figure 1, AI integration in healthcare follows an S-shaped maturity trajectory spanning four key phases: Early Pilot, Initial Scale, Enterprise Roll-out, and Sustainable Integration, that collectively map the evolution of organizational readiness over time.

Diagnostics and Imaging Applications

In radiology, pathology, and other diagnostic fields, AI is already yielding tangible benefits. Many hospitals employ AI tools to streamline the imaging workflow and highlight findings. For example, some radiology departments use AI-enabled cameras or software to automatically position patients in CT or MRI scanners, ensuring the correct orientation

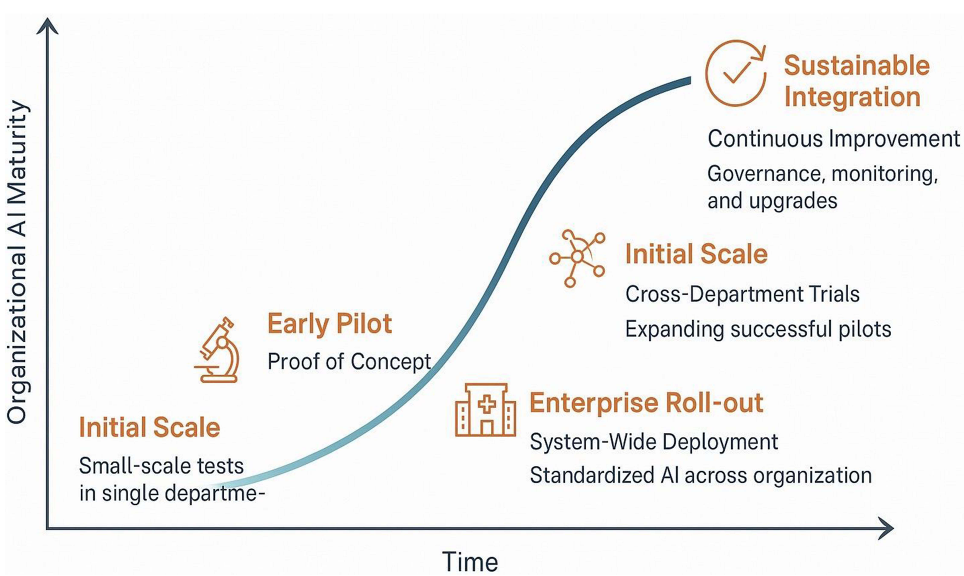

Figure 1 Health System AI Adoption Curve.

and reducing setup errors.[5] Then AI-driven reconstruction algorithms convert lower-dose scans into high-resolution images, improving patient safety without sacrificing image quality (Philips Editorial Team, 2022). In cardiac ultrasound, deep-learning software automatically analyzes heart images to measure chamber volumes and blood flow, tasks that used to require manual tracing.[5] These AI-driven measurements are fast and reproducible, freeing clinicians from repetitive work and allowing them to focus on complex interpretations.

AI is also enhancing cancer screening and detection. For instance, in population-scale breast cancer screening, adding AI to the workflow significantly improved early detection. A German trial involving 463,094 mammograms found that radiologists aided by an AI tool detected 17.6% more cancers than those without AI,[6] with no increase in false positives. This gain (roughly 5.7 to 6.7 cancers per 1000 women) means many more cancers are caught early. Importantly, it came without extra work: the recall rate (the fraction of women called back for further testing) was slightly lower in the AI-assisted group. Traditional screening relies on two clinicians reading each image, and many programs face a shortage of radiologists.[6] By pre-flagging suspicious cases, AI could help alleviate this workload while maintaining, or even improving, accuracy.[6]

Pooled results from a German nationwide cohort (463,094 screens) show that adding an LLM-based triage tool to double reading raised sensitivity from 0.82 to 0.96, equivalent to 5.7 → 6.7 cancers detected per 1000 women, while the recall burden fell slightly (0.06 → 0.05; 38.3 → 37.4 per 1000 screens).[6]

Beyond mammography, AI advances are occurring in many other imaging specialties. In ophthalmology, autonomous AI systems now screen for diabetic eye disease. Three FDA-cleared algorithms can analyze retinal photographs and flag cases of moderate or worse diabetic retinopathy with about 87–90% sensitivity and specificity. These tools have been deployed in clinics and community health programs, helping catch retinal changes in diabetics who might not otherwise see an eye specialist.[7] Researchers in dermatology are testing AI applications for melanoma screening purposes.[8] Smartphone apps and clinical tools can now analyze photos of skin lesions and suggest which ones need biopsy. Early studies show some AI models can match dermatologists at identifying suspicious moles (though regulatory approval and robust validation are still needed before these are in routine clinical use). The common theme is that AI's pattern recognition strengths apply to many kinds of medical images.

AI is also making strides in pathology. In digital pathology labs, machine learning models analyze scanned microscope slides to detect cancer cells and grade tumors. In many studies, these AI systems have matched or even surpassed human pathologists in identifying malignancies. This work is especially important given the global shortage of pathologists. In some countries, pathologists' workloads are so high that slide reviews can take days; AI could pre-screen slides and flag those needing urgent review.[9] For example, an AI program might highlight regions on a tissue slide where a tumor is most likely, allowing pathologists to concentrate on those areas first. Over time, artificial intelligence could speed up diagnosis and help standardize readings across different labs.

AI's role extends beyond any single organ system. For example, algorithms have been developed to automatically measure key parameters, such as ejection fraction from echocardiogram videos and to segment brain lesions on MRI; these tasks previously required laborious manual work.[10–12] Automating such measurements provides consistent, quantitative data to track disease over time. Other AI tools analyze laboratory data; for instance, some systems can count blood cells or identify abnormal cells in images of blood and tissue samples.[13,14] In microbiology, AI is being tested to classify bacteria and predict antibiotic resistance from culture images.[15] These applications show that as long as a task involves pattern recognition, AI can add value, whether on a doctor's screen or in the lab.

Regulatory approvals are on the rise as well. By 2026, dozens of AI diagnostic tools will have received FDA clearance or equivalent international approval. These include software that flags possible strokes on head CT scans and screens for eye disease from fundus photos, as well as algorithms that analyze electrocardiogram (ECG) traces for arrhythmias. For instance, some AI ECG systems can identify atrial fibrillation or even left ventricular dysfunction from a single rhythm strip with accuracy close to a cardiologist.[16] These approvals demonstrate AI's maturing role in clinical practice and pave the way for broader adoption.

Another emerging area is AI triage for routine scans. In busy emergency departments, AI chest X-ray triage systems are being evaluated. One multicenter study of an AI tool (Lunit INSIGHT CXR) categorized chest X-rays as "normal," "non-urgent," or "urgent," achieving about 89% sensitivity and 93% specificity for identifying normal studies.[17]

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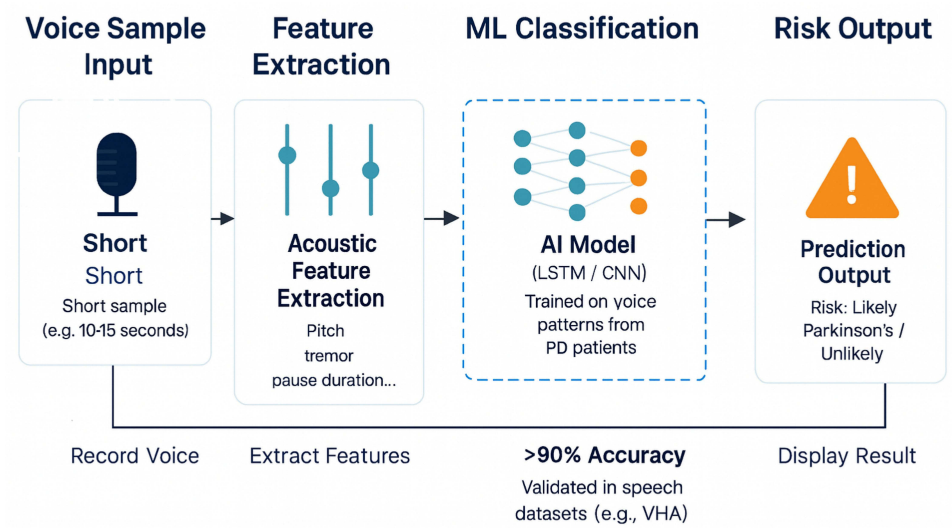

Figure 2 AI Voice Analysis Workflow for Early Parkinson's Detection.

Crucially, this AI reduced radiologists' report turnaround time by roughly half, since clear scans were automatically deprioritized.[17] Similar to this, AI models have demonstrated performance comparable to that of radiologists in identifying intracranial hemorrhage, fractures, and pneumothorax on emergency scans.[18] By filtering out clearly normal images and highlighting acute findings, these systems promise to speed critical diagnoses in high-volume settings.

AI is even venturing into unconventional diagnostic signals. Shen et al's voice analytics study showed that an explainable machine-learning model could identify early Parkinson's disease from brief speech samples with more than 90% accuracy.[19] As illustrated in Figure 2, the diagnostic pipeline begins with a short voice recording and progresses through AI-based acoustic analysis to predict Parkinson's disease risk with over 90% accuracy. Smartphone and wearable usage data tell a similar story: a 23,000-participant observational trial demonstrated that passive keystroke, touch, and motion patterns detected mild cognitive impairment months before standard tests.[20] In laboratory medicine, convolutional networks now segment and classify every leukocyte in a digital smear within seconds, matching expert technologists while processing hundreds of slides per hour.[21] Proteomics adds a further frontier: sparse machine-learning models built on ~3000 plasma proteins improved ten-year risk prediction for dozens of rare and common diseases beyond conventional clinical scores.[22] Together, these examples illustrate how pattern-recognition advances are widening AI's medical footprint beyond imaging and EHR data.

In summary, AI-assisted diagnostics are not limited to one specialty. From automated X-ray triage to mobile ultrasound guidance to smart lab microscopes, the technology is being applied wherever pattern recognition can add value. The key takeaway is that AI tools excel when they take over data-intensive, repetitive tasks and present findings to human experts rather than making autonomous decisions. As clinical trials and real-world studies accumulate evidence, these AI systems will likely become routine diagnostic aids in many settings, helping clinicians catch conditions earlier and more reliably.

Patient Monitoring and Management Applications

AI's impact extends beyond imaging to include patient monitoring and everyday care. Modern wearable devices and home monitors increasingly use machine learning to predict health events before they become emergencies. For instance, advanced continuous-glucose monitors for diabetic patients now do more than track sugar levels: they learn each patient's patterns and can forecast dangerous highs or lows hours in advance.[23] If the system predicts a hazardous sugar swing, it instantly alerts the patient (and, if enabled, the care team) to take corrective action. Similarly, smart heart monitors (patches or watches) with AI can continuously analyze ECG signals or blood pressure trends. These devices can detect subtle arrhythmias or flag early signs of heart failure that might be missed during a brief doctor's visit. AI helps

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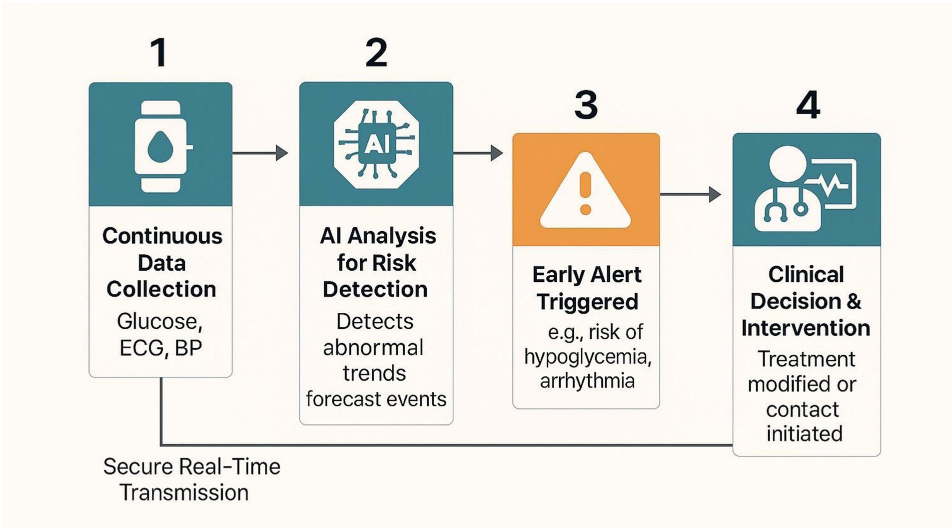

Figure 3 Continuous Monitoring Workflow.

move care from a reactive to a proactive model by turning passive data streams into useful predictions. Figure 3 outlines how wearable or remote devices collect real-time physiological data, which is transmitted to an AI system for continuous risk analysis. When abnormal trends are detected, such as impending hypoglycemia or cardiac instability, the system triggers an early alert, prompting timely clinician review and intervention.

In hospitals and clinics, AI-driven monitoring tools are improving patient safety and efficiency. Researchers have developed AI vision systems, using cameras or smart glasses, to supervise routine clinical tasks in real time. For example, an AI-assisted medication checker can scan a nurse's medication bag and the patient's ID, cross-referencing both to ensure the right drug and dose are given. Early tests of such systems in simulated settings show they catch administration errors instantly,[23] effectively providing a double-check during busy shifts. Similarly, AI cameras are being piloted in operating rooms to detect breaches in sterile techniques or missing instruments, alerting the team before such issues cause harm.[24,25] In intensive care units, AI alarms are being tested to reduce "alarm fatigue": instead of squawking for every small fluctuation, smart algorithms learn each patient's normal patterns and only alert when truly abnormal or dangerous trends appear.[26,27]

Even in low-resource environments, simple AI-enhanced devices are making a difference. Investigators have paired AI algorithms with low-cost pulse oximeters and thermometers to extend critical care to rural clinics. For example, during dengue outbreaks in tropical countries, an AI-enhanced pulse oximeter was able to analyze a patient's vital sign patterns and predict which dengue patients would deteriorate and need intensive care hours in advance.[23] This early warning allows scarce hospital beds and treatments to be reserved for those most at risk. At the public health level, AI analysis of community data is being used to triage vaccine distribution and outbreak responses in real-time, demonstrating that even modest tools can have a big impact when deployed wisely.

Beyond direct monitoring, AI helps manage patient populations and hospital operations. Electronic health records (EHRs) generate so much data that busy clinicians cannot easily spot every pattern. AI analytics now sifts through these records to aid decision-making. For instance, predictive models can flag patients at high risk of readmission or complications (like sepsis) before they leave the hospital, enabling targeted follow-up or preventive therapy.[2] Hospitals also use AI to predict supply needs and manage staffing; on the administrative side, AI is applied to billing and fraud detection. One notable example is IBM's DataProbe, an AI system that looked at billing records from hospitals in the US and found $41.5 million in false Medicare claims in just a few months.[2] These tools reduce waste and free up resources for patient care.

AI is also reshaping telemedicine and virtual care. Many health systems now embed symptom-checker chatbots and self-scheduling assistants in their patient portals; real-world analyses show these tools cut unscheduled emergency visits

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while still offering safe triage advice.[28–30] Prospective studies report that patients who use such apps feel more satisfied with their encounters and experience lower anxiety around care decisions.[31–33] Modeling work further suggests that rerouting even 30% of low-acuity cases could meaningfully ease emergency department crowding.[34] Beyond first contact, "virtual nurses" and AI health coaches are supporting chronic disease management.[35,36] Randomized and pilot trials show that AI messaging apps can improve blood pressure control and medication adherence compared with usual care in hypertension and diabetes.[35,36] A fully automated diabetes-prevention program recently matched human coaching for weight loss and activity over six months.[37] Meanwhile, a parallel trial pairing continuous-glucose monitoring with AI coaching is underway to test long-term metabolic gains.[38] The common thread is round-the-clock, personalized guidance: algorithms learn each user's patterns and adjust reminders or advice in real-time, extending clinical support far beyond the clinic visit.[36,39]

AI is also making inroads in mental health and rehabilitation. Smartphone apps now include AI chatbots that deliver cognitive-behavioral therapy exercises to users with anxiety or depression.[40] Some studies find that people who use these digital "therapists" report measurable improvements in mood and coping skills.[40,41] Similarly, in physical therapy, AI-based motion trackers can analyze a patient's exercise form at home and give real-time feedback, helping prevent reinjury.[42,43] Smart home systems can monitor seniors for falls by analyzing movement patterns; for instance, AI cameras in assisted-living facilities can detect if a resident has fallen out of bed and automatically summon help.[44,45] These innovations extend the reach of healthcare professionals and provide support to patients between their visits.

Integrating AI into monitoring systems requires thoughtful design. Alerts and recommendations must fit into clinicians' normal workflows. Several hospitals are embedding AI outputs directly into their EHR interfaces, so a risk score or alert pops up next to the patient's chart, rather than forcing doctors to use a separate app. Training is also important: physicians and nurses need to understand what an AI alert means and how to respond. Some institutions have set up "AI committees" or liaison teams to guide this education. Over time, as these systems demonstrate value (fewer readmissions, smoother rounds, etc.), clinicians tend to adopt them more readily.

AI-powered monitoring is indeed moving us toward more proactive care. By constantly observing vital signs, symptoms, and behaviors, intelligent systems can catch warning signals that humans might miss. This continuous vigilance has the potential to improve patient outcomes, for example, by preventing hospitalizations, and to make healthcare more efficient. The ongoing challenge is to deploy these tools in ways that respect patient privacy and integrate smoothly into care, but the examples above show that meaningful progress is already being made.

Robotic Surgery and Therapeutic Applications

AI is also advancing beyond the operating room. Modern surgical robots (such as the da Vinci system) give surgeons highly precise control of instruments but traditionally still require a human hand for every movement. The next step is to make these systems "smart" with AI enhancements. One major area is visual assistance: researchers have trained AI to enhance the surgical view in real time. For example, an AI model can denoise and clarify the live endoscopic video feed, removing blur from instrument motion or smoke from cauterization.[46] It can also adjust the colors or contrast to highlight blood vessels and nerves. This clear, augmented view helps surgeons see fine structures that might otherwise be obscured, reducing the chance of accidental damage.

Beyond improving visibility, AI is enabling new degrees of automation. While fully autonomous surgery remains a future goal, parts of procedures can now be partially automated under supervision. In lab demonstrations, robots have used AI to autonomously suture wounds or perform bone cuts along pre-planned lines. In one experiment, an AI-driven system performed a running suturing task as well as expert surgeons.[47] (A human operator was standing by to supervise, but the success shows how reliable certain subtasks can become). Similarly, AI algorithms can analyze the surgeon's hand movements in real time.[48–50] If the algorithm detects tremor or fatigue, it can stabilize the robot's motion, smoothing out small unintentional movements.[51] This kind of assistance could reduce fatigue-related errors in long procedures.

AI also aids in surgical planning and navigation. Machine learning models can analyze patient scans to create customized guides. For instance, in orthopedic surgery, AI algorithms generate a 3D model of a patient's hip or knee from CT data and help design a perfectly fitting cutting guide or implant. AI has been utilized in neurosurgery to dynamically map brain anatomy: a study trained an AI using surgical ultrasound and electrical impedance data to distinguish tumor tissue from normal brain in real time.[46] During an operation, this tool can highlight the tumor boundary, guiding the surgeon in removing the right amount of tissue. In spinal surgery and ENT procedures, similar AI tools align a patient's preoperative images with live tracking to ensure each cut follows the planned safe path.

The robotics utility extends to postoperative care and rehabilitation. In rehabilitation, AI-powered exoskeletons are being refined to support patients recovering from stroke or spinal injury, adjusting assistance in real time to each individual's gait patterns.[52] Smart prosthetic limbs with embedded intelligence translate electromyographic or cortical signals into smoother, more intuitive movements; Capsi-Morales et al demonstrated a system that decodes muscle activity on-the-fly, enabling natural hand control with high precision.[53] Mullin et al further showed that a myoelectric arm can learn from residual muscle signals to drive a robotic hand in real time, achieving gesture accuracy above 90%.[54] In radiation oncology, it was reported that AI-based auto-contouring software cuts target-definition time to minutes while preserving dosimetric quality.[55] Collectively, these augmented-reality cameras, semi-autonomous robots, adaptive rehab devices, and AI-planned therapies illustrate how intelligent systems continue to widen the boundaries of surgical and restorative care.

Early indicators suggest these innovations can translate into better outcomes. Experts generally agree that the continued integration of AI into surgery and therapy will enhance patient safety and efficacy.[46] Initial clinical reports are encouraging: teams using AI-assisted navigation have observed shorter operative times and fewer small complications. For example, one center reported that robotic laparoscopic procedures guided by AI had less blood loss and shorter hospital stays on average.[56] In gastrointestinal endoscopy, AI systems that analyze colonoscopy video in real-time have already been shown in trials to increase the rate at which doctors detect precancerous polyps, reducing the chance that a patient goes home with an undetected lesion.[57–59] Furthermore, AI models predicting patient outcomes have helped tailor interventions. They forecast that postoperative pain or infection risk can prompt preemptive measures, improving recovery.[60,61]

In the post-operative setting, AI algorithms are being deployed to stratify risk, utilizing continuous vital sign and lab data to predict potential complications.[62,63] By flagging these patients early, care teams can intervene, for example, by adjusting medications or ordering more frequent checkups, before a small problem becomes a crisis.[64] This type of AI is already available for general wards and ICUs, demonstrating how the technology extends from the operating room into the entire patient recovery pathway.

AI in surgery and therapy is about augmenting every step of the surgical journey. Rather than replacing surgeons, these tools serve as digital assistants, helping clinicians work more accurately and freeing them to focus on the human aspects of care. From real-time vision enhancement to automated suturing demonstrations, each AI innovation adds up to safer, more efficient procedures. The ultimate measure will be patient outcomes, and so far, early results and expert consensus are promising that AI-enhanced care will improve those outcomes over time.

Implementation Strategies, Challenges, and Considerations

Despite the promise of AI, translating research prototypes into routine healthcare practice has hurdles. A primary issue is data integration. Medical records, imaging, and device outputs are often stored in incompatible formats across different hospital systems. Bringing all this data together for AI requires extensive data engineering, cleaning, standardizing, and annotating records so algorithms can learn from them. At the same time, every data-prep step should tag age, sex, ethnicity, and geography so that later performance dashboards can surface subgroup drift. Patient privacy is another top concern. Healthcare organizations must implement strong de-identification and security measures so that AI training does not risk exposing personal information.[2] Techniques like federated learning (where an AI model is trained across multiple sites without sharing raw data) are being explored to address this, but they remain complex to deploy.

Leadership Roadmap for AI Adoption: A Four-Phase Pathway

The following roadmap (Figure 4) outlines the four stages health systems must navigate to scale AI safely: urgency, coalition, pilot, and scale.

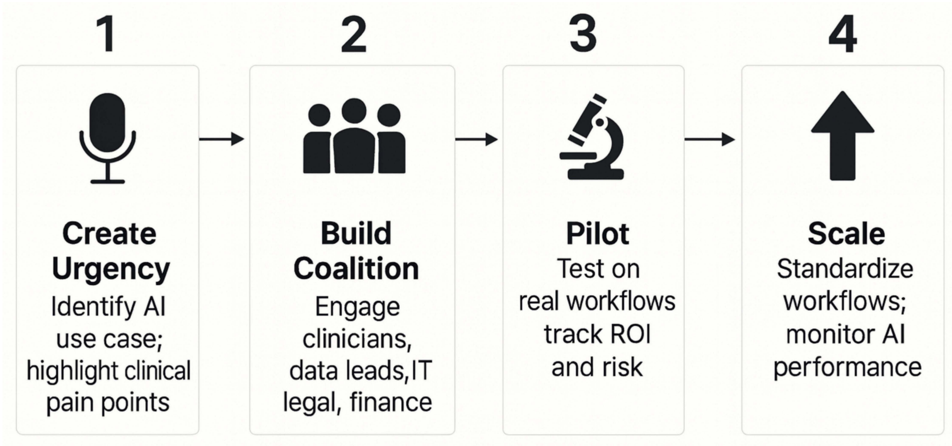

Figure 4 AI Leadership Roadmap: A 4-Phase Adoption Strategy.

Create Urgency: Quantify Local Pain

Leaders first surface a problem that frontline teams already feel but have not yet measured. At Kaiser Permanente, anonymous time-motion logs showed physicians devoting 43% of their workdays to documentation; introducing ambient LLMs scribes reclaimed 15,791 hours in a single year, or roughly 1794 clinician days.[65] Similar numbers emerged in German breast-screening hubs, where AI-supported double reading raised detection from 5.7 to 6.7 cancers per 1000 women without extra recalls, underscoring both patient safety and throughput dividends.[6] Publicly sharing these local metrics at grand rounds or board retreats transforms diffuse frustration into a quantified performance gap that demands executive action.

Build A Coalition—Lock In Multidisciplinary Ownership

Momentum stalls if urgency rests on a single champion. Successful sites convene a steering group that pairs C-suite sponsors with mid-level clinical leaders, data scientists, equity officers, and patient advocates.[66] In one mammography network, radiographers and community liaisons helped shape recall-letter language, while finance directors mapped time savings to budget cycles. Equity specialists pre-agreed on subgroup performance thresholds, preventing late-stage fairness surprises.[67] Formalizing roles, meeting cadence, and KPIs at this stage converts enthusiasm into shared accountability.

Pilot-Test In High-Signal, Low-Risk Settings

Pilots mirror the target workflow yet remain small enough for weekly iteration. An ICU introduced a machine-learning alarm suppressor on two pods; within six weeks, false alarms fell by 60% with no missed critical events.[68] A spinal cord injury unit trialed AI motion tracking during home rehab and documented significant gains in upper-limb strength compared with standard exercise videos.[43] In virtual care, an AI symptom checker embedded in the patient portal cut non-urgent ED visits among chemotherapy patients, boosting satisfaction scores.[69] Each pilot tracks operational (minutes saved, visits avoided), clinical (sensitivity, adverse events), and human-factor metrics (trust, satisfaction). Dashboards refresh monthly and disaggregate by age, sex, and ethnicity to surface bias early. To help CFOs and board committees translate technical promise into accountable value, Table 1 distills total-cost-of-ownership elements, an average ROI benchmark of USD 3.20 returned within 14 months for every dollar spent on healthcare AI, and the governance checkpoints required to track those savings over time.[1]

Scale—Institutionalize Governance, Infrastructure, And Education

After regulatory compliance is confirmed, governance becomes routine rather than ad hoc: quarterly model-performance reviews, annual bias audits, and real-time drift alerts feed the quality committee. Cloud or on-prem compute budgets move from innovation funds to the operating ledger, aligned with cybersecurity controls.[70] Education widens beyond early adopters; mandatory micro-learning teaches every clinician to interpret and override AI outputs. Financial officers

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Table 1 Financial Stewardship Checklist for AI Deployments: Key TCO Elements, Typical 3.2:1 ROI Within 12–18 months, and Governance Checkpoints From Business-Case Approval to Annual Reinvestment

Financial Stewardship Element	Guidance & Benchmark Numbers
Total cost of ownership (TCO)	Budget ≈ license fee × (1 + 0.5 integration and security + 0.2 training).
Baseline & pay-back	Use a fully loaded clinical salary (≈ USD 120/hour). A 15,000-hour documentation pilot yields ~USD 1.8 M gross value. Median ROI across enterprise AI projects is **3.2:1** with a 12–18-month payback.
Variable costs	Plan 0.1 × license per annual model retraining and bias audit.
CapEx vs OpEx split	Capitalize integration/cyber spend; treat hosting, monitoring, and audits as operating expenses to smooth cash flow.
Governance gates	1) The CFO/quality committee approves the pre-investment business case. 2) Quarterly variance review triggers re-tuning if savings drift **±10%**. 3) Annually reinvest ≥**15%** of realized savings in workforce or equity initiatives.
Reporting	Finance and clinical leads co-publish ROI, quality, and equity metrics to the board dashboard each quarter.

Notes: Bold values represent critical financial metrics: 3.2:1 = target ROI ratio; ±10% = acceptable variance range; ≥15% = minimum reinvestment requirement.

embed the 3.2:1 ROI expectation into budget forecasts, reallocating gains to sustain licensing and retraining fees. Progress dashboards, hours returned to care, alarm reductions, and triage accuracy are featured in staff newsletters and board packets to preserve urgency. Finally, an "AI product owner" coordinates updates so that new versions do not fracture across departments.

Threading Ethics And Equity

Equity checkpoints appear in every phase: diverse data selection during urgency framing, subgroup dashboards during pilots, and public reporting once at scale. Telestroke services in rural networks, for example, now require quarterly audits showing no performance drop compared with urban centers, linking adoption to access improvement.[71]

Outcome

By anchoring urgency in local metrics, broadening ownership, validating with rigorously measured pilots, including telehealth and rehabilitation exemplars, and scaling under disciplined governance and ROI targets, leaders turn AI from experimental gadgetry into a strategic, equitable asset that satisfies boards, regulators, and bedside teams alike.

Other Challenges and Considerations

Bias and fairness are also significant challenges. Because AI learns from historical data, it can inadvertently perpetuate disparities present in that data. For example, if an AI model for imaging diagnosis was trained mostly on data from urban hospitals, it might underperform when used on patients in rural areas or from underrepresented ethnic groups. Studies have documented cases where medical AI tools were less accurate for certain races or ages.[72,73] Steering committees must set a "red-flag" threshold, eg, ±5% drop in sensitivity for any demographic group, which triggers model retraining or workflow rollback. Quarterly equity reports should be presented at the same board meeting that reviews infection control or readmission metrics, signaling that fairness carries equal governance weight. Addressing this requires deliberate effort: developers must use diverse training datasets, and models should be continuously tested on different patient populations. Professional societies and regulators increasingly emphasize fairness checks. Any implemented AI tool should come with documentation of its performance across subgroups and with a plan for monitoring its real-world outcomes.

Building clinicians' trust in AI is another hurdle. Most AI tools have been validated retrospectively (on archived data), but clinicians rightly want to see them succeed in real-time patient care. Although prospective clinical trials of AI are still relatively rare, their numbers are increasing. For example, the breast cancer screening study mentioned earlier was effectively a real-world trial of AI in practice.[6] Trust also rises when frontline staff see disaggregated accuracy on a shared dashboard and can escalate equity concerns via a rapid-response ticket. Meanwhile, many hospitals are gradually introducing AI by having it pre-screen X-rays or lab results and flag notable cases instead of allowing the AI to make final diagnoses. This "AI as second reader" approach lets doctors get used to the tool's suggestions without relinquishing responsibility.[74] Over time, evidence of benefit and transparency about limitations helps build confidence. Even now, survey data indicate that most doctors see AI as a helpful aid rather than a threat, provided it comes with clear guidelines and oversight.

Practical infrastructure is also a consideration. High-performance computing power and secure data storage are needed, especially for image-heavy and genomics AI. Some solutions rely on cloud computing, which means hospitals need fast, reliable internet and strong cybersecurity. The upfront costs for software licenses, hardware, and workforce training can be substantial, especially for smaller or rural hospitals. However, many institutions find that successful AI tools pay for themselves over time through efficiency gains. For instance, by reducing duplicate tests or catching billing errors, hospitals can recoup initial investments. One survey reported that top-performing AI healthcare deployments achieved an average return on investment of roughly USD 3.20 for every USD 1.[1] This demonstrates that financial incentives can align with innovation, although the path to those savings must be managed carefully.

Ethical and legal issues also require attention. Patients should ideally be informed when AI is used in their care and understand its role. Currently, most AI systems function as "black boxes", providing recommendations without reasoning that is easily interpretable Efforts in "explainable AI" are trying to address this by providing at least some understandable rationale (for example, highlighting which features led to a prediction).[9] Another unresolved issue is liability: who bears responsibility if an AI-based recommendation results in an incorrect diagnosis: the doctor, the hospital, or the AI developer? In most current practice, the physician remains ultimately accountable, but legal standards will evolve. Some regions are already developing guidelines to clarify these issues. For now, the best practice is clear communication: doctors should not defer blindly to AI, and patients should know that a human is making the final judgment.

Another challenge is that AI models evolve. Once deployed, an AI system may drift in performance as new data or patient populations are seen. For example, if a hospital changes its imaging equipment or treats a different mix of diseases, the AI's accuracy could degrade. This means hospitals must continuously monitor AI accuracy and be prepared to retrain models with new data. Regulatory agencies like the FDA have proposed frameworks for ongoing post-market surveillance of AI devices, treating them more like dynamic systems than static machines. In practice, this adds a new layer of quality assurance—akin to how hospitals regularly calibrate lab instruments, they will need to audit AI systems on an ongoing basis.

Education and workforce training are also essential. Community-stakeholder panels, including patients, caregivers, and advocacy groups, should preview AI outputs and language to ensure cultural relevance before go-live. Many hospitals create multidisciplinary teams, including data scientists, IT experts, and clinicians, to oversee AI projects. Clinicians need training on how to use AI tools safely and interpret their outputs.[75] Some medical schools and professional societies are now introducing AI literacy into their curricula.[76] The World Health Organization and ITU have collaborated on AI in healthcare guidelines,[77] and standards bodies are extending healthcare data standards (like HL7 FHIR) to support AI.[78] These governance and training efforts are part of the broader infrastructure needed to make AI work in real-world healthcare.

Finally, broader policy and social context matter. Many countries have launched digital health strategies that include AI components. For example, Canada's national AI strategy includes various healthcare projects, while the European Union's Horizon programs provide funding for health AI research. Funding agencies, such as the US NIH, have established special programs for AI in medicine that promote the creation of large shared databases. The looming global shortage of health workers, projected to exceed 10 million by 2030,[1] motivates AI adoption, especially in underserved areas. We are seeing pilot models where AI-assisted telemedicine extends specialists' reach to rural clinics. All these efforts, technical, organizational, and policy, must come together. The organizations that succeed will be those that approach AI as part of a larger system: setting up beneficial data pipelines, training staff, establishing ethical oversight, and aligning incentives, rather than just dropping algorithms in isolation.

Conclusion

AI already improves detection, monitoring, and clinical workflows, proving its value alongside skilled clinicians. Successful adoption hinges on disciplined governance, multidisciplinary oversight, rigorous validation, and transparent performance tracking so that algorithms remain accurate, equitable, and trustworthy. Used this way, AI frees clinicians from repetitive data tasks and lets them focus on nuanced decision-making and patient connection.

As every past medical innovation required training and a cultural shift, so will AI. The goal is augmentation, not replacement: a radiologist with an AI reader, a nurse with an AI triage assistant, or a surgeon with AI-guided navigation. Future research must prioritize long-term prospective trials demonstrating clinical outcomes, real-world fairness audits across diverse populations, and standardized frameworks for AI lifecycle governance. With vigilant oversight and continuous learning, healthcare can harness AI to deliver safer, faster, and more personalized care, expanding access while preserving the human touch at the heart of medicine.

Ethical Statement

This narrative review analyzed only publicly available sources and involved no human participants, animals, or patient-identifiable data; therefore, institutional ethics approval and informed consent were not required.

Author Contributions

All authors contributed significantly to the reported work, including conception, study design, execution, data acquisition, analysis, and interpretation; participated in drafting, revising, or critically reviewing the article; provided final approval of the version to be published; agreed on the journal for submission; and accepted accountability for all aspects of the work.

Disclosure

The authors report no conflicts of interest in this work.

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