Palliative and Advanced Illness Research Center

Using artificial intelligence and predictive analytics to promote diagnostic excellence for older adults

NASEM Workshop on Advancing Diagnostic Excellence for Older Adults

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  - NIH (NHLBI, NIA)
  - The Alzheimer's Association
  - University of Pennsylvania and Penn Medicine
- Conflicts of interest
  - None

TABLE 5-1 Opportunities to Reduce Diagnostic Error Through Electronic Clinical Documentation

Role for Electronic Documentation	Goals and Features of Redesigned Systems
Providing access to information	Ensure ease, speed, and selectivity of information searches; aid cognition through aggregation, trending, contextual relevance, and minimizing of superfluous data.
Recording and sharing assessments	Provide a space for recording thoughtful, succinct assessments, differential diagnoses, contingencies, and unanswered questions; facilitate sharing and review of assessments by both patient and other clinicians.
Maintaining dynamic patient history	Carry forward information for recall, avoiding repetitive patient querying and recording while minimizing copying and pasting.
Maintaining problem lists	Ensure that problem lists are integrated into workflow to allow for continuous updating.
Tracking medications	Record medications that the patient is actually taking, patient responses to medications, and adverse effects in order to avert misdiagnoses and ensure timely recognition of medication problems.
Tracking tests	Integrate management of diagnostic test results into note workflow to facilitate review, assessment, and responsive action as well as documentation of these steps.
Ensuring coordination and continuity	Aggregate and integrate data from all care episodes and fragmented encounters to permit thoughtful synthesis.
Enabling follow-up	Facilitate patient education about potential red-flag symptoms; track follow-up.
Providing feedback	Automatically provide feedback to clinicians upstream, facilitating learning from outcomes of diagnostic decisions.
Providing prompts	Provide checklists to minimize reliance on memory and directed questioning to aid in diagnostic thoroughness and problem solving.
Providing placeholder for resumption of work	Delineate clearly in the record where clinician should resume work after interruption, preventing lapses in data collection and thought process.
Calculating Bayesian probabilities	Embed calculator into notes to reduce errors and minimize biases in subjective estimation of diagnostic probabilities.
Providing access to information sources	Provide instant access to knowledge resources through context-specific "infobuttons" triggered by keywords in notes that link user to relevant textbooks and guidelines.

"The committee concluded that health IT has the potential to impact the diagnostic process in both positive and negative ways…

Despite this potential, however, there have been few demonstrations that health IT actually improves diagnosis in clinical practice."

NASEM. *Improving Diagnosis in Health Care* 2015.

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The state of clinical AI

- Billions of dollars invested
- Tens of thousands of peer-reviewed publications
- Only a handful of published RCTs, not all suggesting benefit of AI system
- Hype far exceeds evidence

Source: https://commons.wikimedia.org/wiki/File:Reflection_in_a_soap_bubble_edit.jpg

Tran BX et al. *J Clin Med*. 2019;8(3):360.
Cristea IA et al. *Eur J Clin Invest*. 2019;e13072.
Genin K, Grote T. *Philosophy of Medicine* 2021;2(1).

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ARTICLE

Pivotal tri

detection

Michael D. Abràmoff

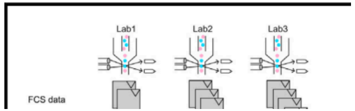
Article n for

Patterns

Knowledge transfer to enhance the performance of deep learning m

B cell neoplasm

Graphical abstract



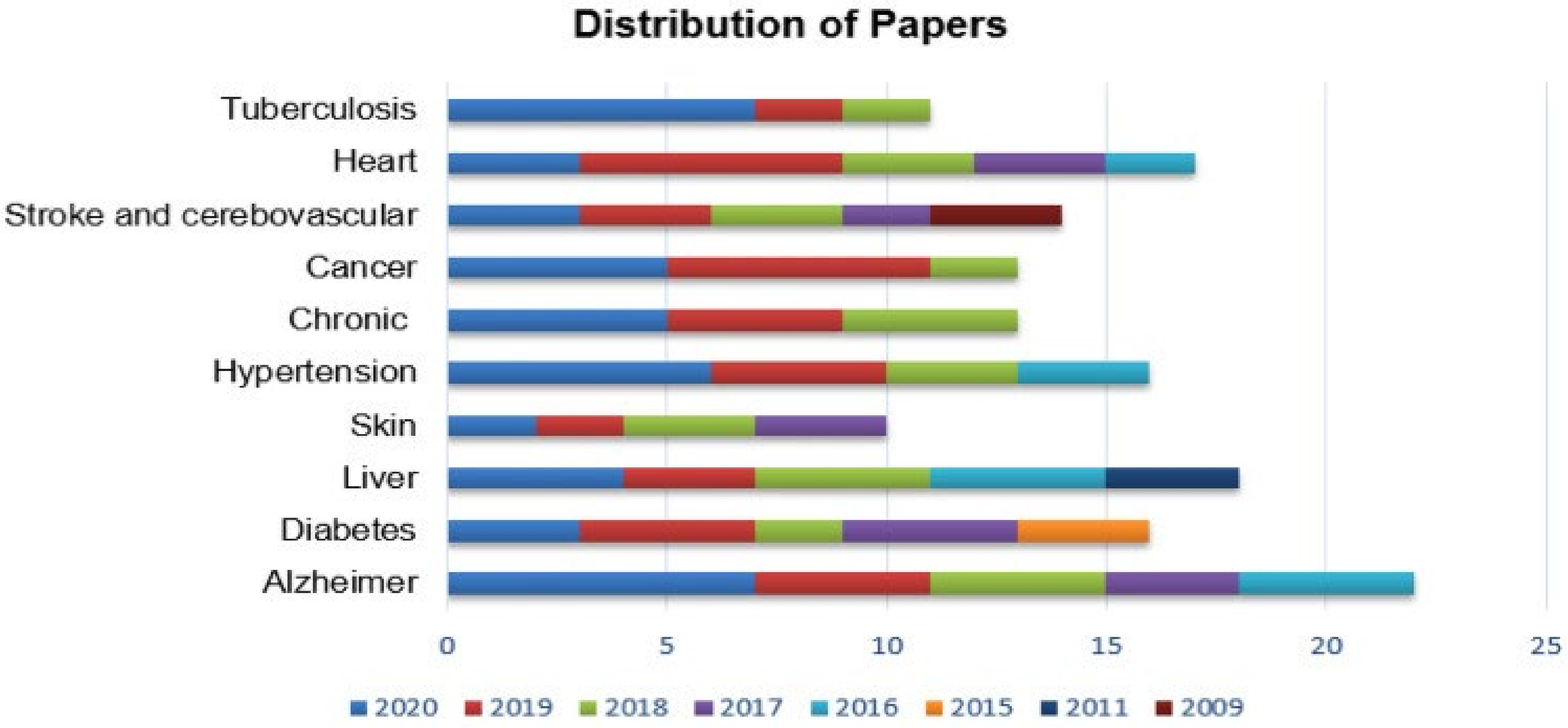
Home > Radiology: Artificial Intelligence > VOL. 4, NO. 3

Original Research

Artificial Intelligence with Statistical Confidence Scores for Detection of Acute or Subacute Hemorrhage on Noncontrast CT Head Scans

Eli Gibson, Bogdan Georgescu, Pascal Ceccaldi, Pierre-Hugo Trigan, Youngjin Yoo, Jyotipriya Das, Thomas J. Re, Vishwanath RS, Abishek Balachandran, Eva Eibenberger, Andrei Chekkoury, Barbara Brehm, Uttam K. Bodanapally, Savvas Nicolaou, Pina C. Sanelli, Thomas J. Schroeppel, Thomas Flohr, Dorin Comaniciu, Yvonne W. Lui

See fewer authors



Kumar Y et al. *J Ambient Intell Humaniz Comput* 2022;1–28.

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Current knowledge: rules-based CDSS

- Prescribing practices aligned with Beers Criteria
- Palliative care referral
- High-risk anti-depressant medication prescribing
- Deprescribing and medications reviews
- Delirium
- Falls prevention
- Functional decline
- Post-acute care transitions
- Pressure ulcers

Singhal S et al. *JAGS* 2022. Tan A et al. *BMC Med Inform Decis Making* 2020.
VanDaele MA et al. *Mental Health Clinician* 2021. Damoiseaux-Volman BA et al. *JMIR Medical Informatics* 2021.
McDonald EG et al. *JAMA Internal Medicine 2022.*

Current knowledge: AI-based CDSS

Diagnosis of

nutrition-related syndromes

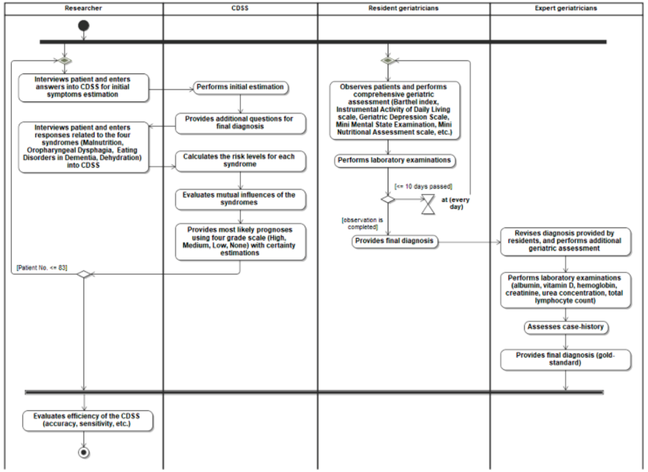


Figure 1. The procedure of experimental evaluation of the proposed CDSS.

Diagnosis of

need for palliative care

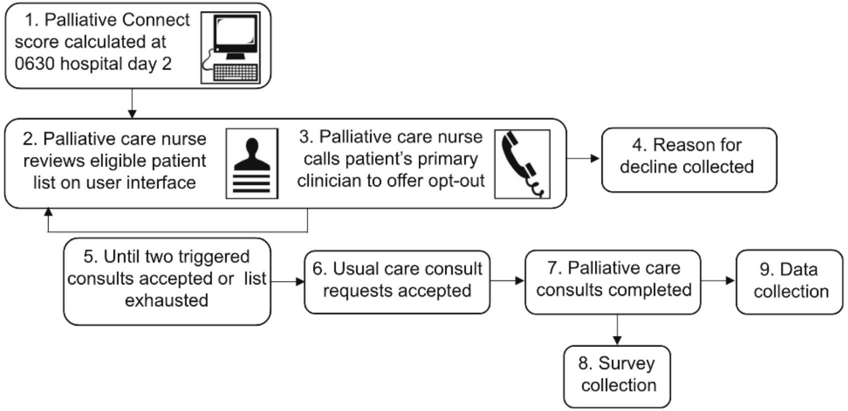


Figure 1 Study process flow for palliative connect intervention. Each weekday, a Palliative Connect score (predicted risk of death within 6 months) was calculated for patients on hospital day 2. Patients with a score ≥ 0.3 populated a web-based user interface list in order from highest to lowest risk (actual prediction not shown). The palliative care team's triage nurse called the primary clinicians of patients in descending order to offer an opt-out of the triggered consult until the maximum of two consults were accepted. Remaining patients were carried over on the list each day until they were offered a triggered consult, or they were discharged or transferred to another service. Consults requested per usual care were accepted. Palliative care clinicians and hospitalists completed surveys and clinical data was obtained from the clinical data warehouse.

Penn
UNIVERSITY of PENNSYLVANIA

Petrauskas V et al. *Appl Sci* 2021.

Courtright KC et al. *JGIM* 2019.

The pair Center

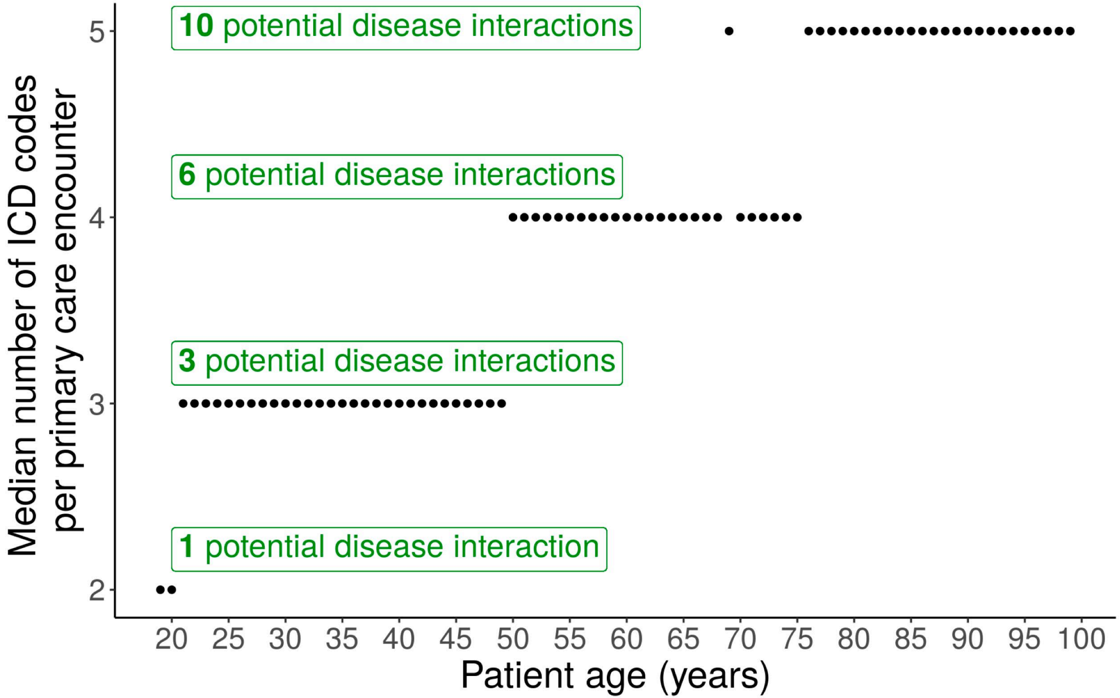
Challenges specific to older adults

- Broad diagnostic scope
- Higher comorbidity count
- Higher variation in functional status
- Uncertainty in prognosis and life expectancy
- Less gold-standard data from clinical trials due to age exclusions
- Higher prevalence of cognitive impairment
- Higher probability of care fragmentation
- Higher probability of (and possibly need for) caregiver involvement

Lipman HI et al. *Journal of Geriatric Cardiology* 2015.

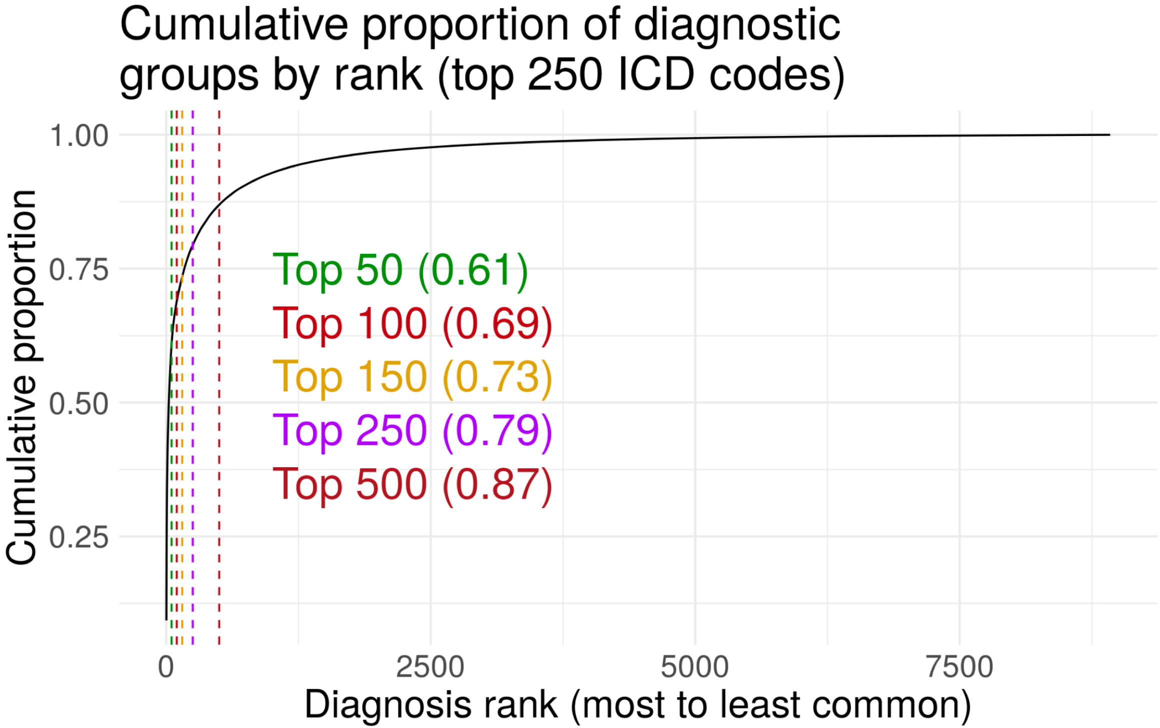
Diagnostic scope and complexity increase with age

- In a sample of 571,543 primary care encounters in Penn Medicine from 2020-2021
- The median number of diagnoses at each encounter increases linearly with age
- The complexity, or number of of potential disease interactions, increases geometrically with age



Diagnostic scope in primary care

- 177,965 primary care encounters in Penn Medicine (FY 2020) among those age ≥ 65
- Internal Medicine, Geriatric Medicine, Family Medicine, and Penn Primary Care groups
- Most common 250 ICD codes collapsed into 150 clinically relevant diagnostic categories, the rest are individual ICD codes



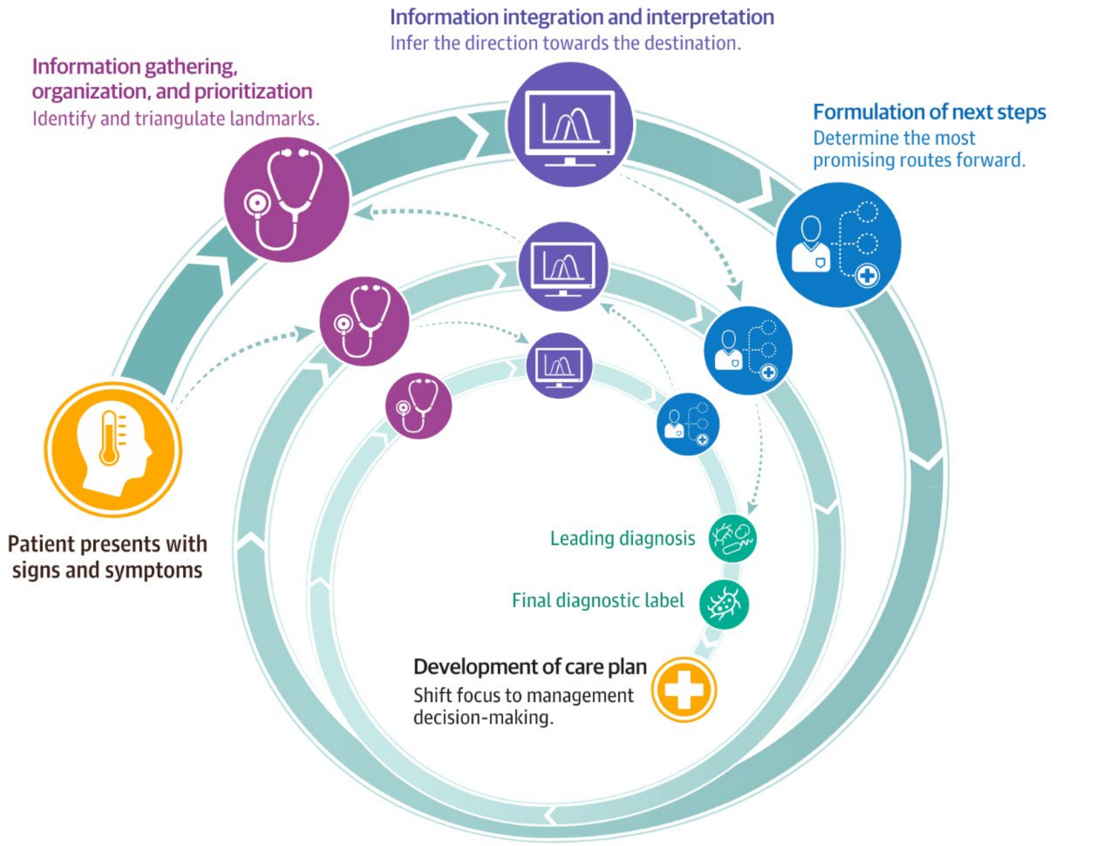
Text analysis: documented signs and symptoms

- Convenience sample of 40,000 outpatient encounter notes in UPHS (2018-2019) among individuals age ≥ 65
- UMLS Metathesaurus to identify signs and symptoms in clinical text
- Most common signs and symptoms ranked by prevalence

Text feature	Count	Cumulative %
Dyspnea	33,671	9.1%
Wheezing	25,744	16.1%
Exanthema	17,663	20.9%
Chest pain	15,054	25.0%
Sore to touch	14,607	29.0%
Symptoms	11727	32.2%
Headache	9592	34.8%
Discharge, body substance	9468	37.4%
Fatigue	8717	39.7%
Chills	8237	42.0%
Abdominal pain	7973	44.1%

Weissman GE et al. *Unpublished* 2022.

Figure. The Dynamic Diagnostic Refinement Process



Diagnosis as collaborative, iterative, wayfinding

Adler-Milstein J et al. *JAMA* 2021.

Four Life Cycle Phases of Artificial Intelligence Model Deployment Incorporating Human Factors Elements and User-centered Design

Life Cycle Phase	Description	Example User-Centered Design Methods and Techniques
Design	The intended user of the AI should be involved early and continuously during this stage to ensure their needs are considered.	Observe the clinical environment Identify needs through interviews and focus groups Develop user personas
Development	Rapid and iterative prototyping of an AI model to maintain desired performance characteristics through testing with intended end-users.	Conduct iterative user testing Perform cognitive walkthrough Perform final (summative) usability testing
Implementation	Technical integration, testing and deployment, educational sessions for users, and consideration of interaction with other clinical systems, tools, and work processes.	Redesign existing workflows and processes to integrate new technology Conduct pilot test Refine based on user feedback
Long-term use	AI models should be continually monitored and validated to maintain desired performance and to detect safety events. Models may be retrained and additionally re-evaluated for modification of human factors elements.	Monitor user interaction data Provide a mechanism to report safety issues Monitor performance outcomes

Next steps: AI diagnostic CDSS

- Strong regulatory environment to ensure accountability
- RCTs needed to establish safety, effectiveness, and equity
- Transparency and reproducibility to promote access, innovation, and trust

Next steps: specific to older adults

- Broad diagnostic scope vs disease-specific
- Models trained on data from older adults
- Clinician-, patient-, and caregiver-facing interfaces
- Integration with workflows relevant to older adults (primary care, nursing home, home health)