Ore 16.00 – 18.00

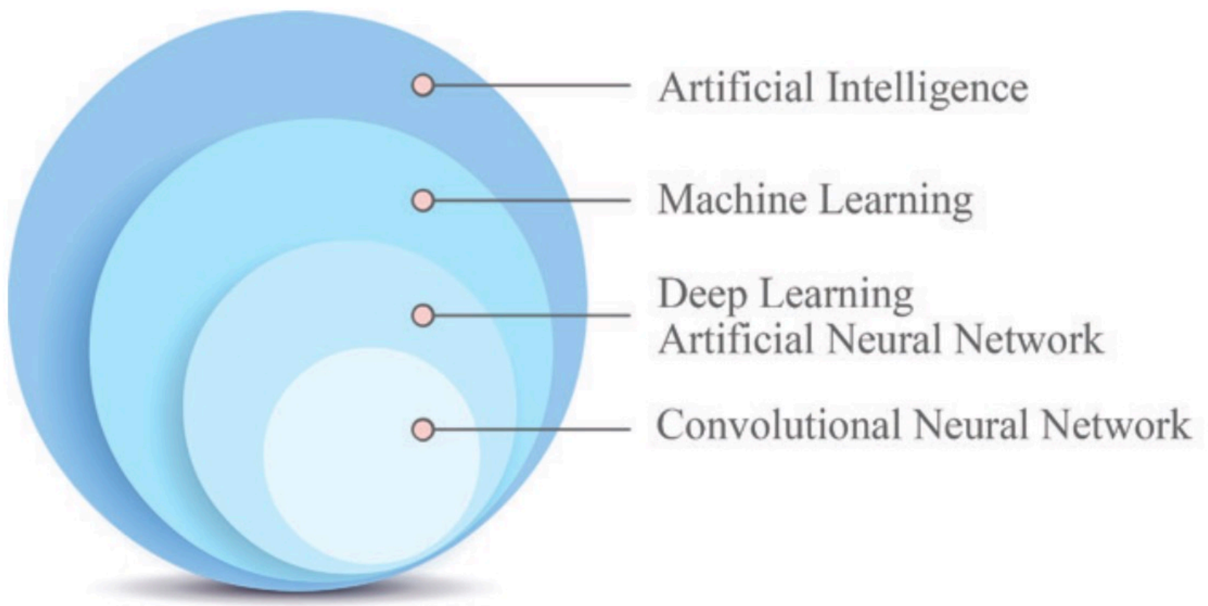
**NUOVE TECNOLOGIE ED AI: TRA OPPORTUNITÀ E RISCHI
LE NUOVE FRONTIERE DELLA RESPONSABILITÀ**

Presiedono	
Vasco Giannotti	*Presidente Forum Risk Management in Sanità*
Fabio Canini	*Ministero della Salute*
Intervengono	
Federico Gelli	*Direttore Direzione Generale Sanità, Welfare e Coesione sociale Regione Toscana*
Maurizio Hazan	*Studio Legale Taurini Hazan, Presidente Fondazione Italia in Salute*
Pasquale Giuseppe Macrì	*Responsabile Centro Gestione Rischio Clinico Regione Toscana, Membro Tavolo Tecnico Ministero della Salute*
Marco Rossetti	*Consigliere 3° Sezione Civile Cassazione*
Andrea Simoni	*Segretario Generale Fondazione Bruno Kessler*
Daniela Bardoni	*Patrocinante in Cassazione- Associazione Sanitas et Cura*
Riccardo Ferrari	*Esperto in AI applicato alla radiodiagnostica AO San Camillo Forlanini RM*
Gaia Fiorinelli	*Sant'Anna Pisa*

Dott. Riccardo Ferrari
Radiodiagnostica Emergenza Urgenza
Az. Osp. San Camillo Forlanini- Roma
Presidente *della sezione di Informatica ed intelligenza artificiale in Radiologia della SIRM 2025-2026*
Membro della *commissione Intelligenza artificiale in Radiodiagnostica della SIRM*
Membro del *Board degli esperti per un nuovo codice deontologico FNMOCEO*
Docente *Scuola di Specializzazione in Radiodiagnostica "Sapienza" Università di Roma*

PRINCIPI GENERALI

Perché questo grande interesse dell’AI in medicina ed in particolare, Perché la radiologia sta facendo da pioniere per l’AI in medicina?



Società Italiana di Radiologia Medica

Sezione di Studio
Gestione delle Risorse ed
Economia Sanitaria in Radiologia

2012-2014

SINOSSI

LINEE GUIDA PER LA DEMATERIALIZZAZIONE DELLA DOCUMENTAZIONE CLINICA IN DIAGNOSTICA PER IMMAGINI

NORMATIVA E PRASSI

Presidenza del Consiglio dei Ministri

CONFERENZA PERMANENTE PER I RAPPORTI TRA LO STATO, LE REGIONI E LE PROVINCE AUTONOME DI TRENTO E BOLZANO

I radiologi lavorano nell’ambiente più digitalizzato della Medicina

Ezekiel Emanuel, uno degli inventori del Affordable Care Act, oncologo ed esperto di bioetica alla Università della Pennsylvania afferma al meeting dell’ACR del 2016 che il machine learning potrà ***“sostituire molto del lavoro dei radiologi”***

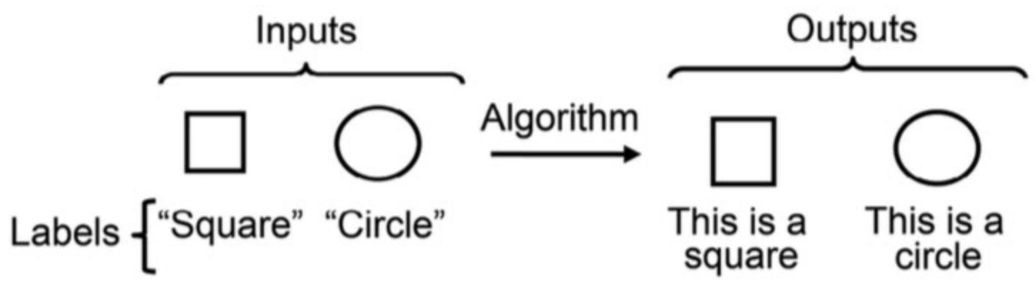
Machine learning

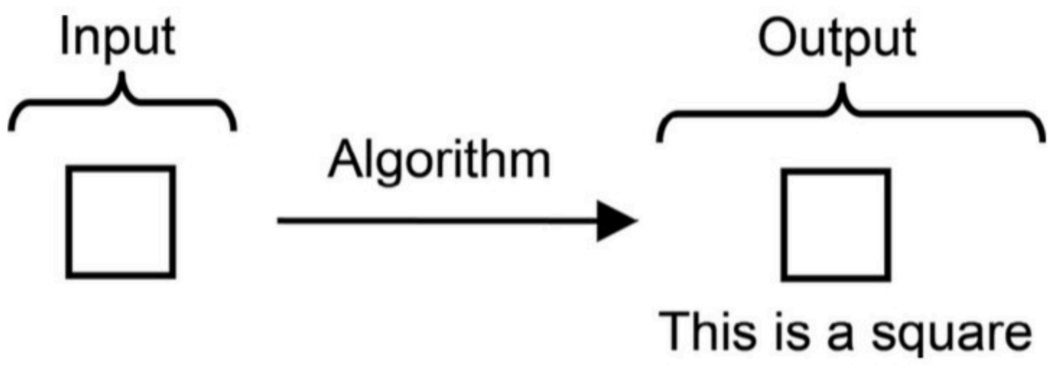
Machine learning (1959 by Arthur Samuel): *“campo di studio che fornisce ai computer l’abilità di imparare senza essere esplicitamente programmati”*

Supervisionati:
Necessitano di input ed output definiti e addestramento manuale

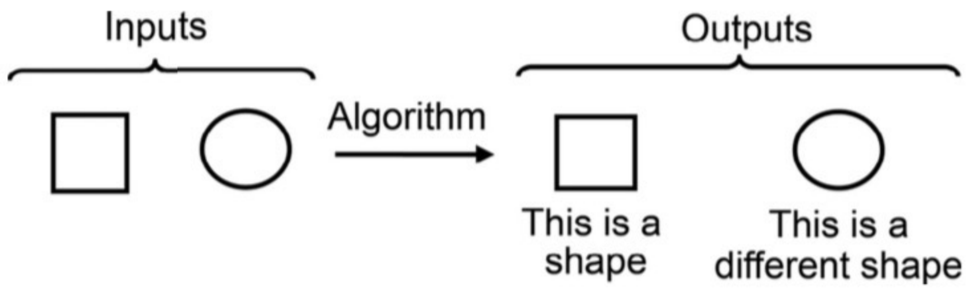
Non supervisionati:
Hanno solo l’output definito

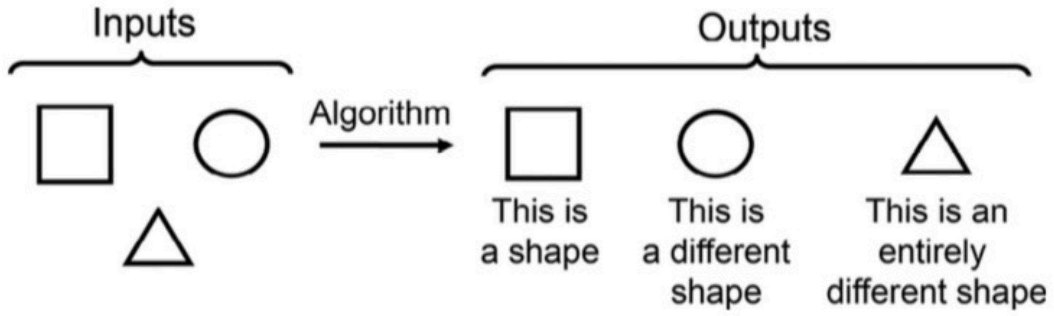
Training

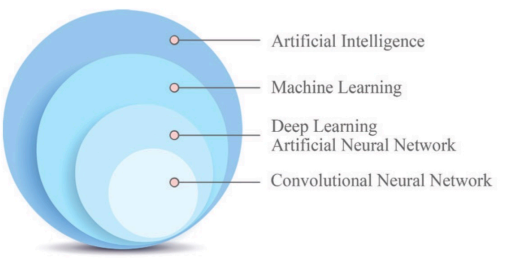




Training





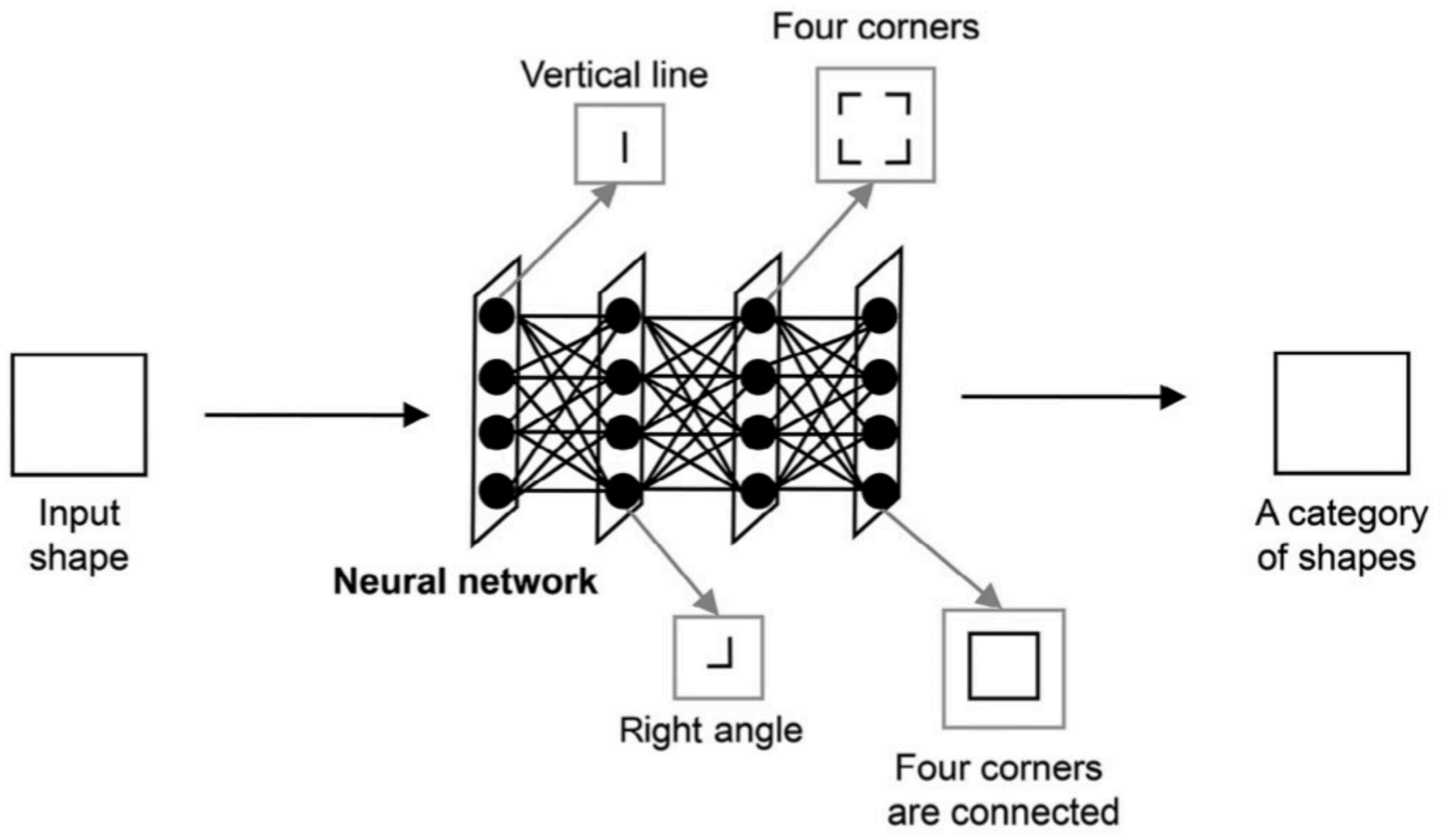


Deep learning artificial neural network

Livelli multiprocessori che imparano a riconoscere la rappresentazione dei dati con diversi processi di astrazione.
Basati sulla rappresentazione dei dati piuttosto che su precisi algoritmi.
Necessità di moltissimi dati per imparare e altissime potenze di calcolo (almeno 20 livelli).

Convolutional neural network

Sono categorie particolari di reti neurali particolarmente efficienti con l'interpretazione delle immagini.



La radiologia medica (2023) 128:755–764
https://doi.org/10.1007/s11547-023-01634-5

COMPUTER APPLICATION

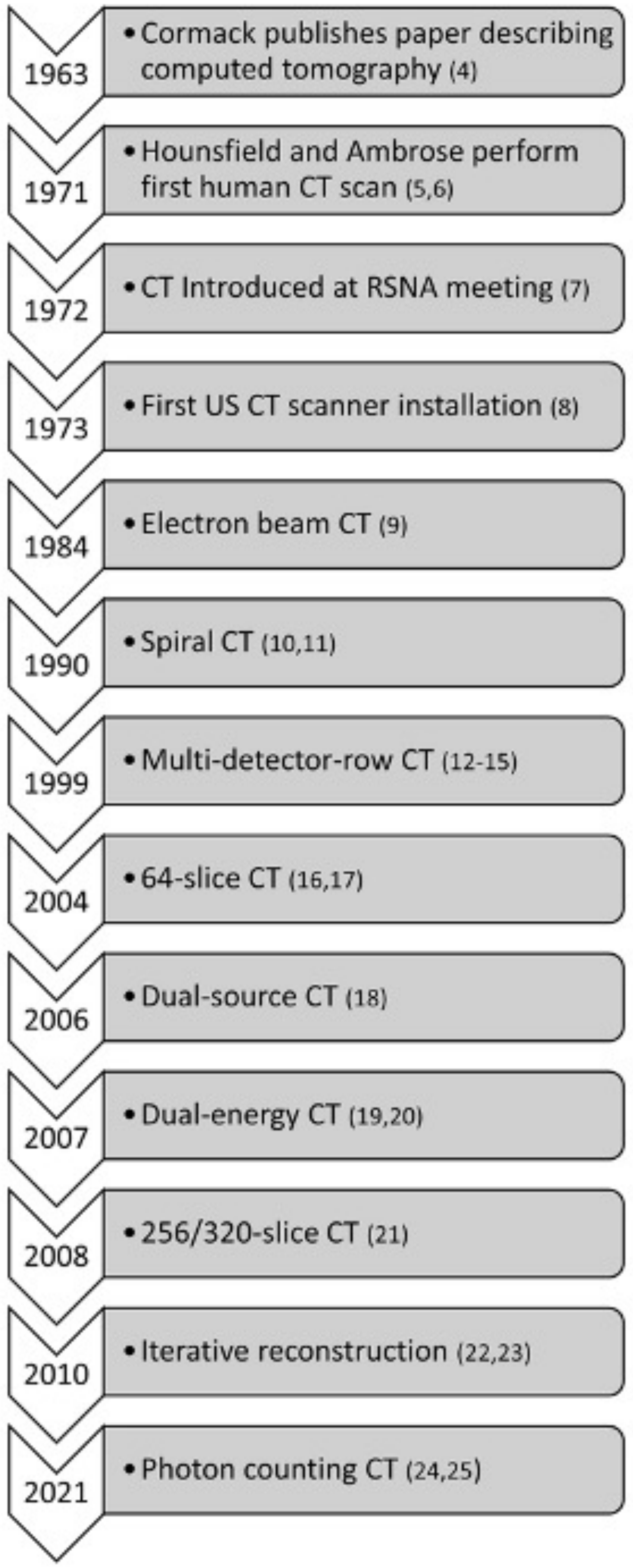
Explainable AI in radiology: a white paper of the Italian Society of Medical and Interventional Radiology

Emanuele Neri[1] · Gayane Aghakhanyan[1] · Marta Zerunian[2] · Nicoletta Gandolfo[3] · Roberto Grassi[4] · Vittorio Miele[5] · Andrea Giovagnoni[6] · Andrea Laghi[2] · SIRM expert group on Artificial Intelligence

Received: 17 February 2023 / Accepted: 19 April 2023 / Published online: 8 May 2023

VANTAGGI DELL'USO DELL'INTELLIGENZA ARTIFICIALE

- La radiodiagnostica sta aumentando la mole di dati da analizzare in maniera esponenziale
- A breve non sarà possibile interpretarli solo scorrendo le migliaia di immagini
- Automazioni necessarie per poter integrare le immagini con dati clinici
- Sempre maggiori classificazioni di malattie, e loro aggiornamenti
- Ergonomia ed interfaccia uomo macchina deve essere semplificata



SISTEMA SANITARIO REGIONALE
AZIENDA OSPEDALIERA SAN CAMILLO FORLANINI

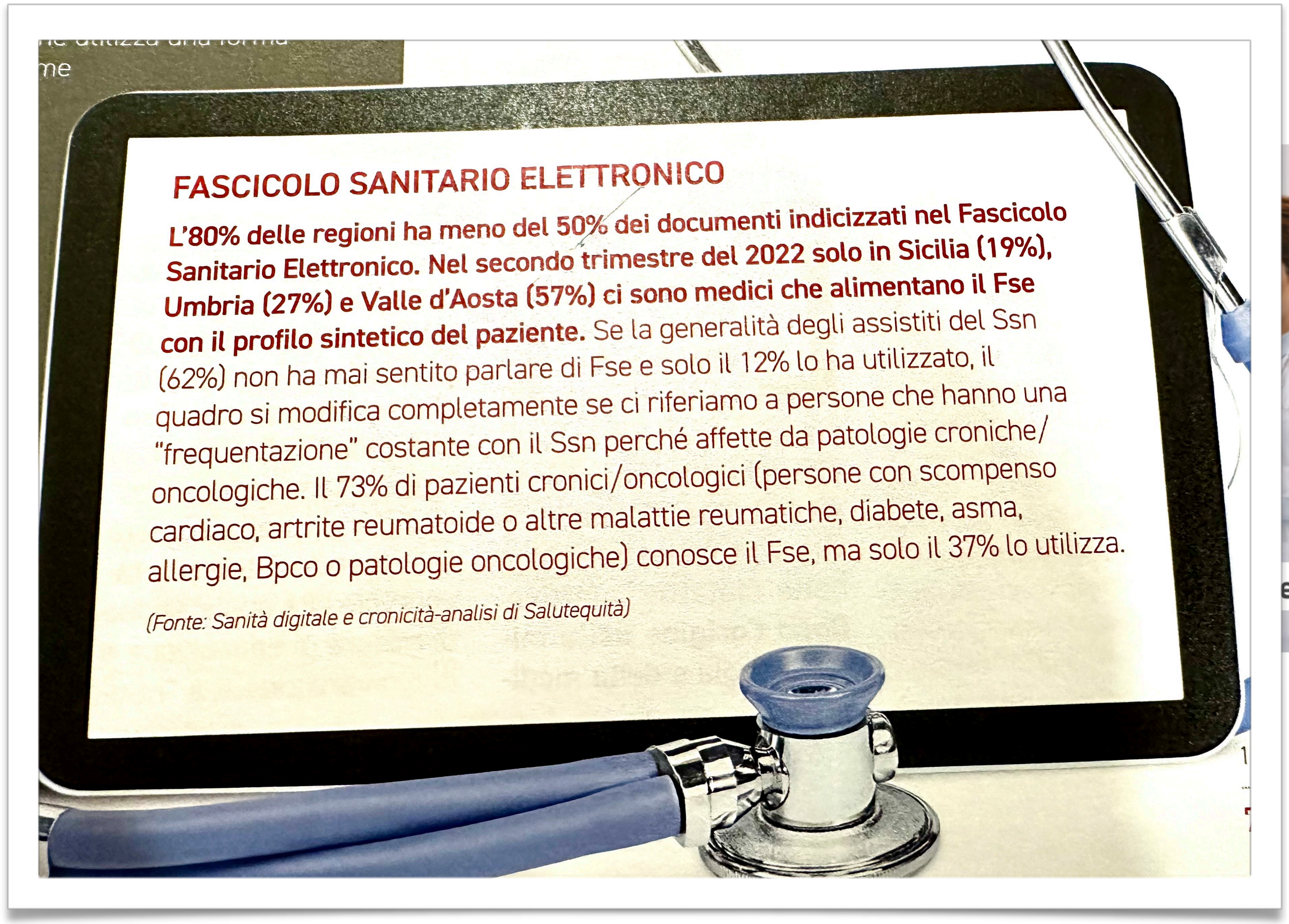
AI e medicina: digitalizzazione

Società Italiana di Radiologia Medica e Interventistica

PNRR - Salute
Piano Nazionale di Ripresa e Resilienza

Italia domani – Piano Nazionale di Ripresa e Resilienza
Finanziato dall'Unione europea NextGenerationEU
Cerca

Home | Come cambia il Servizio sanitario nazionale | Missione salute | Riforme | Investimenti | Bandi e avvisi | Norme e atti | Notizie


FASCICOLO SANITARIO ELETTRONICO

L'80% delle regioni ha meno del 50% dei documenti indicizzati nel Fascicolo Sanitario Elettronico. Nel secondo trimestre del 2022 solo in Sicilia (19%), Umbria (27%) e Valle d'Aosta (57%) ci sono medici che alimentano il Fse con il profilo sintetico del paziente. Se la generalità degli assistiti del Ssn (62%) non ha mai sentito parlare di Fse e solo il 12% lo ha utilizzato, il quadro si modifica completamente se ci riferiamo a persone che hanno una "frequentazione" costante con il Ssn perché affette da patologie croniche/oncologiche. Il 73% di pazienti cronici/oncologici (persone con scompenso cardiaco, artrite reumatoide o altre malattie reumatiche, diabete, asma, allergie, Bpco o patologie oncologiche) conosce il Fse, ma solo il 37% lo utilizza.

(Fonte: Sanità digitale e cronicità-analisi di Salutequità)

Come cambia il **Servizio sanitario nazionale**

LIMITI DELL'INTELLIGENZA ARTIFICIALE

- **Variabilità biologica**
- **Variabilità tecnica** di acquisizione delle immagini in particolare di RM il cui segnale è relativo e le cui immagini necessitano di processi di omogenizzazione per essere confrontabili; ma anche i protocolli di somministrazione di mdc in TC sono piuttosto varibili e rischiano di dare in pasto informazioni non omogene alle macchine.
- **Database** necessario ad imparare per i software di IA, che vuol dire mettere insieme tanti casi con le medesime patologie.
- **Tematiche Medico Legali**
- **ETICA!!**

Le domande:

1) Il nostro lavoro è solo riconoscere le immagini patologiche e seguire le flowchart diagnostiche?

2) Può essere scisso da considerazioni cliniche e mediche anamnestiche?

3) Non è necessaria la comunicazione e l'empatia con il paziente?

Radiology: Artificial Intelligence EDITORIAL

Will Artificial Intelligence Replace Radiologists?

Curtis P. Langlotz, MD, PhD

From the Department of Radiology, Stanford University, 300 Pasteur Dr, Room H1330D, Stanford, CA 94305. Received April 9, 2019; revision requested April 16; revision received April 16; accepted April 17. **Address correspondence to** the author (e-mail: *langlotz@stanford.edu*).

Conflicts of interest are listed at the end of this article.

Radiology: Artificial Intelligence 2019; 1(3):e190058 • https://doi.org/10.1148/ryai.2019190058 • Content code: IN

The question of whether Machines Can Think is about as relevant as the question of whether Submarines Can Swim.

Edsger Dijkstra, 1984

Computer-aided Detection for Mammography: A Cautionary Tale

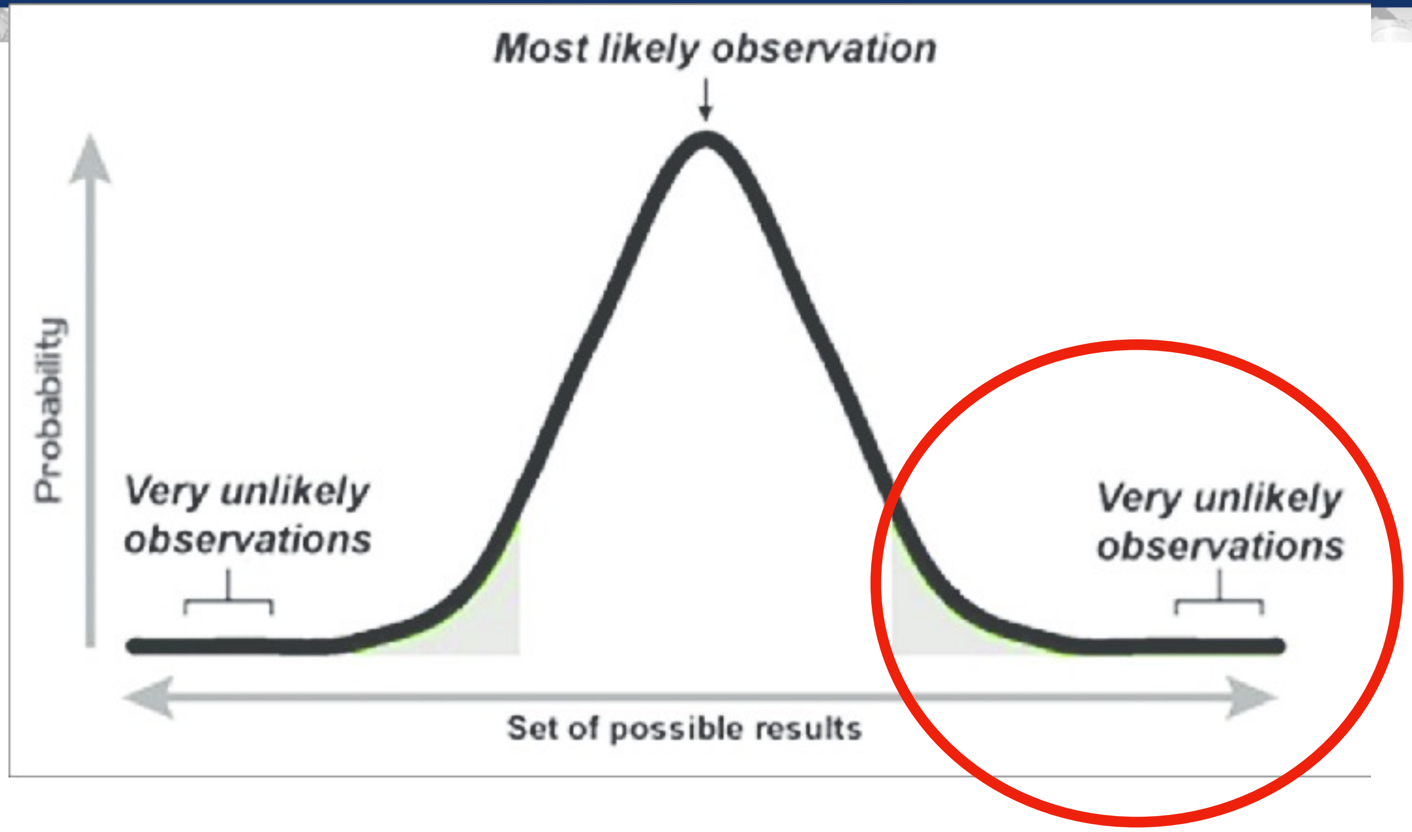
Concerns in the 1990s about the variable quality of mammography interpretation (10) led to two key steps forward: (a) the Breast Imaging Reporting and Data System

L'intelligenza Artificiale sostituirà i radiologi?

Bradley Erickson, Director of the Radiology Informatics Lab at Mayo Clinic told me that some of the hype we hear from some of the machine learning and deep learning experts saying that AI would replace radiologists is for them looking at radiologists as just looking at pictures. *That would be me saying while I look at programmers, all they do is typing, so we can replace a programmer with a speech recognition system*, he added. Langlotz compared the situation to that of the autopilot in aviation. The innovation did not replace real pilots, it augmented their tasks. On very long flights, it is handy to turn on the autopilot, but they are useless when you need rapid judgment. So, the combination of humans and machines is the winner solution. And it will be the same in healthcare.

Thus, I agree with Langlotz completely when he says that *artificial intelligence will not replace radiologists. Yet, those radiologists who use AI will replace the ones who don't*. Let me show you why.

"…Artificial intelligence will not replace radiologists. Yet, those radiologists who use AI will replace the ones who don't…"



Radiology: Artificial Intelligence
EDITORIAL

Will Artificial Intelligence Replace Radiologists?

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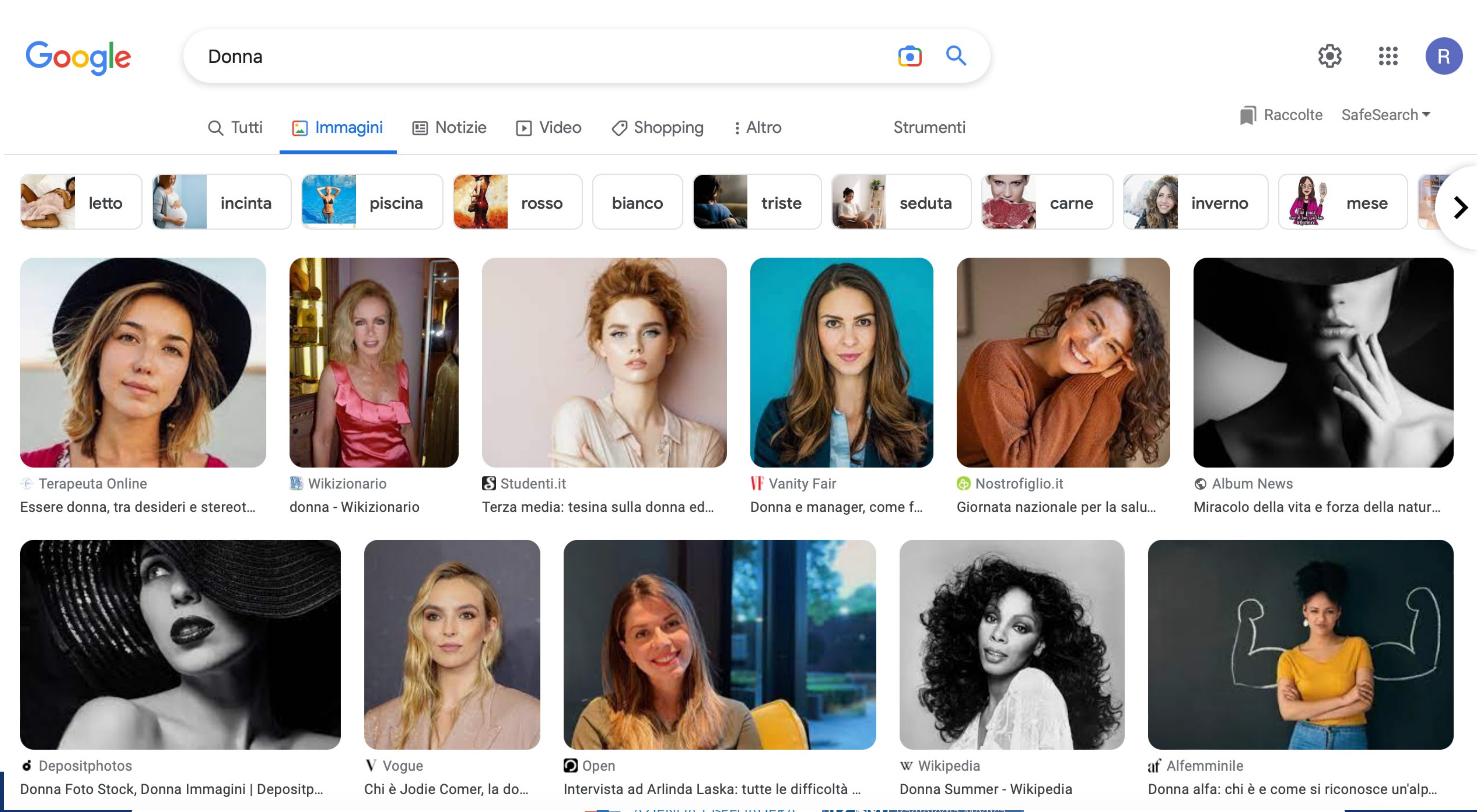
Radiologists Know "The Long Tail"

These assessments dramatically oversimplify what radiologists do. A comprehensive catalog of radiology diagnoses lists nearly 20000 terms for disorders and imaging observations and over 50000 causal relations (20).

But human radiologists are also trained to detect uncommon diseases **in the long tail** of the distribution, including rheumatoid arthritis, sickle cell disease, and post-transplantation lymphoproliferative disorder.


Google
Donna
Tutti
Immagini
Notizie
Video
Shopping
Altro
Strumenti
Raccolte
SafeSearch
letto
incinta
piscina
rosso
bianco
triste
seduta
carne
inverno
mese
Terapeuta Online
Essere donna, tra desideri e stereot...
Wikizionario
donna - Wikizionario
Studenti.it
Terza media: tesina sulla donna ed...
Vanity Fair
Donna e manager, come f...
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Giornata nazionale per la salu...
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Vogue
Chi è Jodie Comer, la do...
Open
Intervista ad Arlinda Laska: tutte le difficoltà ...
Wikipedia
Donna Summer - Wikipedia
Alfemminile
Donna alfa: chi è e come si riconosce un'alp...

INTERAZIONE COMPUTER-UMANO CHE NON FUNZIONA

PILOTA AUTOMATICO IN AVIAZIONE

Piuttosto di ridurre il loro coinvolgimento, molti piloti rilevano che l'automazione ne ha accresciuto il coinvolgimento ed il carico di lavoro soprattutto nelle fasi più delicate di atterraggio e decollo.

"Non fu errore umano, il software era difettoso": così è caduto il Boeing

Il ministro etiope del Trasporti ha anticipato i risultati delle indagini preliminari sull'incidente: "I piloti hanno lottato fino all'ultimo"

Lo schianto del volo dell'Ethiopian Airlines, nel quale hanno perso la vita 157 persone, non è stato causato da un errore umano.

Secondo il rapporto preliminare sulle **cause dell'incidente** del volo 302, i piloti "hanno ripetutamente attuato le procedure raccomandate da Boeing, ma non sono riusciti a controllare il velivolo", che è precipitato al suolo, vicino ad Addis Abeba, solamente sei minuti dopo il decollo.

Il ministro dei Trasporti etiope, Dagmawit Moges, ha dichiarato che "non si è trattato di un errore umano, bensì di un difetto di software". L'attenzione torna quindi sul **sistema anti-stallo**, già sotto la lente di ingrandimento degli inquirenti e delle Nazioni, che poco dopo lo schianto avevano lasciato a terra tutti i **Boeing 737 Max 8**, perché dotati dello stesso sistema di volo, che già in precedenza aveva causato un incidente aereo. Secondo la prima ricostruzione,"il pilota ha tentato varie volte di disattivare il controllo automatico del volo, che ha spinto l'aereo in picchiata pochi minuti dopo il decollo" e ha fatto "diversi tentativi di riprendere il controllo del velivolo". Ma l'attivazione di **picchiata**, avvenuta in automatico, non ha lasciato scampo.

INTERAZIONE COMPUTER-UMANO CHE FUNZIONA

On January 15, 2009, Captain Chesley “Sully” Sullenberger landed an Airbus A320-214 in New York’s freezing Hudson River following a bird strike-induced loss of both engines. All 155 passengers and crew on board US Airways Flight 1549 survived.

Why the ‘Miracle on the Hudson’ in Sully was No Crash Landing

by The Conversation | Jul 18, 2017 | The Conversation

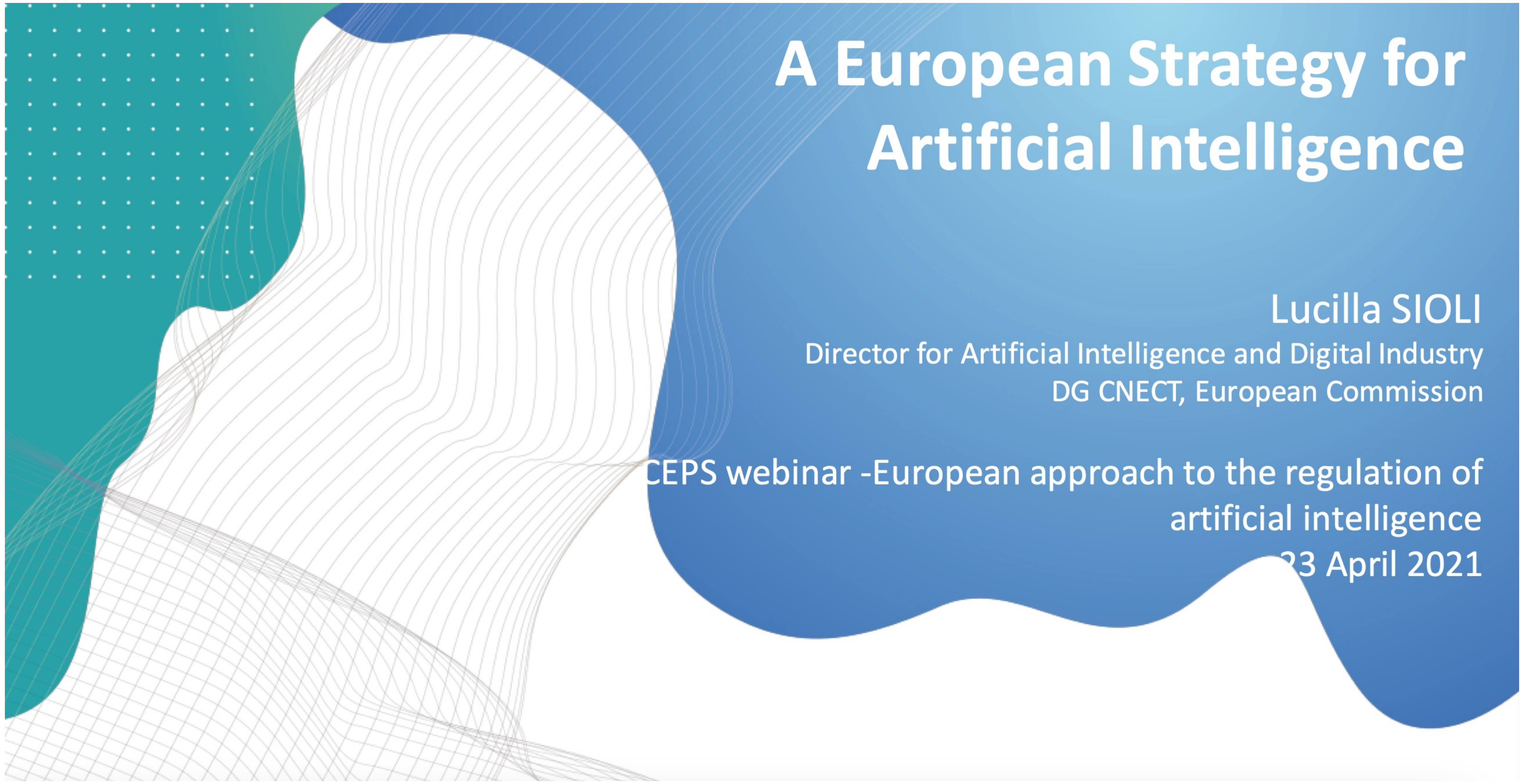
The real miracle

The miracle was enabled because of an optimal system response comprising many human and non-human parts. As is always the case in such recoveries, the human element was central in holding the system together.

LEGISLAZIONE E LINEE GUIDA

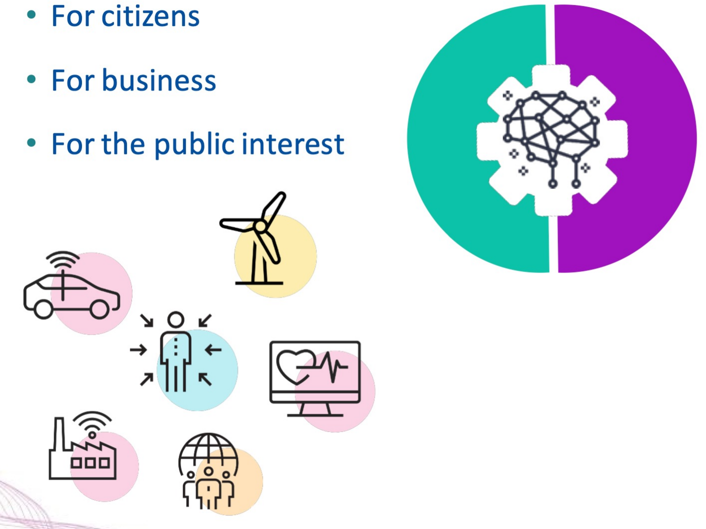
What is the EU AI Act?

The AI Act is a proposed European law on artificial intelligence (AI) – the first law on AI by a major regulator anywhere. The law assigns applications of AI to three risk categories. First, applications and systems that create an **unacceptable risk**, such as government-run social scoring of the type used in China, are banned. Second, **high-risk applications**, such as a CV-scanning tool that ranks job applicants, are subject to specific legal requirements. Lastly, applications not explicitly banned or listed as high-risk are largely left unregulated.



AI is good …

- For citizens
- For business
- For the public interest

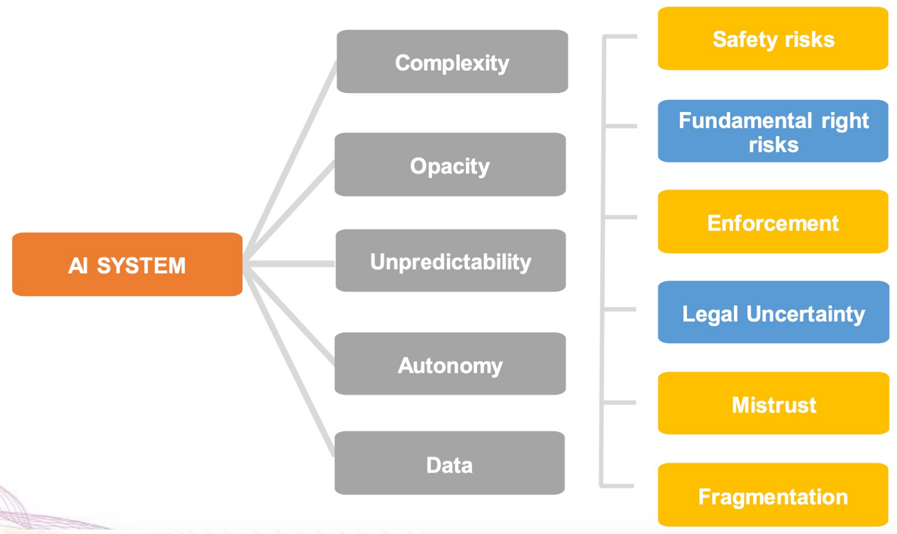


… but creates some risks

- For the safety of consumers and users
- For fundamental rights

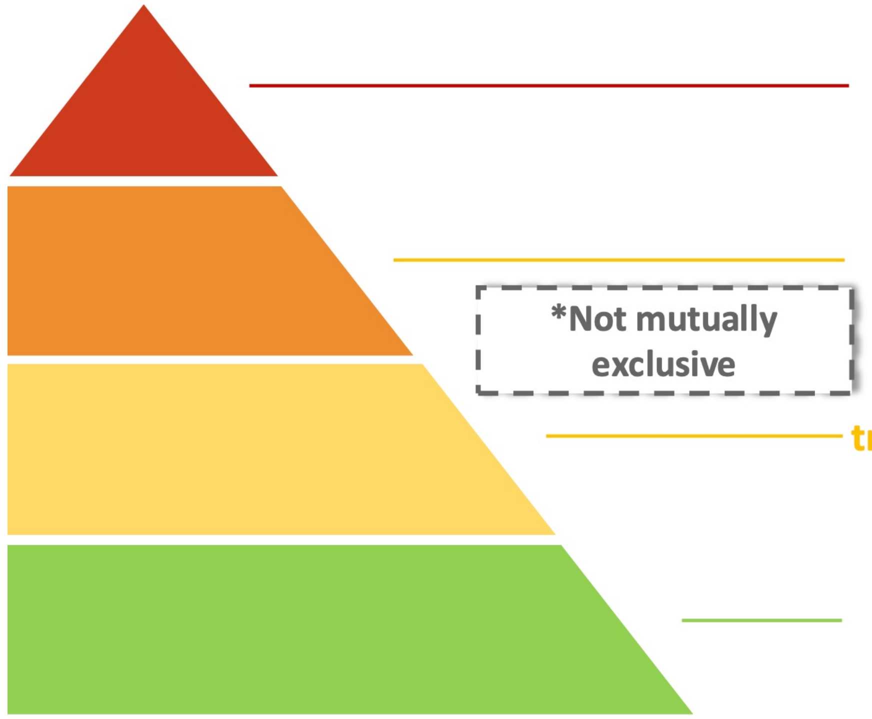
European Commission

Why do we regulate AI use cases?



European Commission

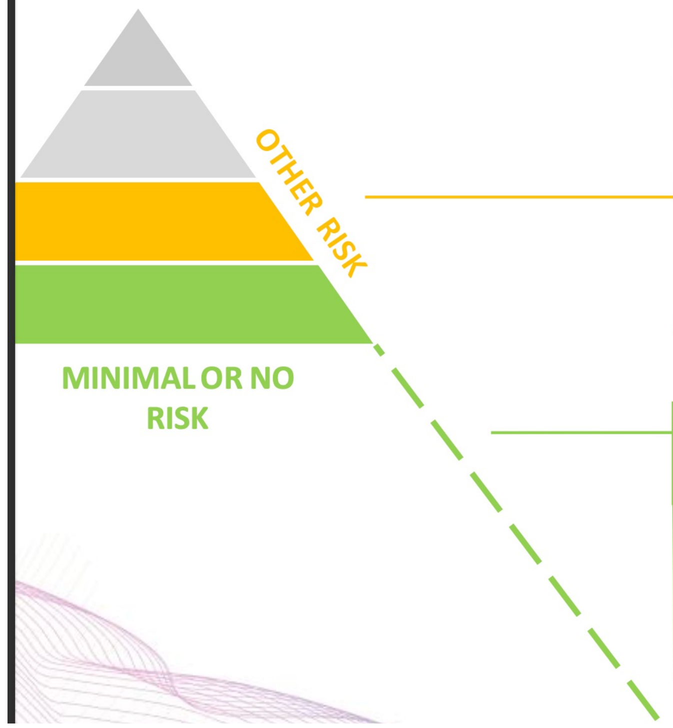
A risk-based approach to regulation



Unacceptable risk e.g. social scoring	**Prohibited**
High risk e.g. recruitment, medical devices	**Permitted** subject to compliance with AI requirements and ex-ante conformity assessment
AI with specific transparency obligations 'Impersonation' (bots)	**Permitted** but subject to information/transparency Obligations
Minimal or no risk	**Permitted** with no restrictions

European Commission

Most AI systems will not be high-risk (Titles IV, IX)



New transparency obligations for certain AI systems (Art. 52)

- **Notify humans** that they are **interacting with an AI system** unless this is evident
- Notify humans that emotional recognition or biometric categorisation systems are applied to them
- Apply **label to deep fakes** (unless necessary for the exercise of a fundamental right or freedom or for reasons of public interests)

Possible voluntary codes of conduct for AI with specific transparency requirements (Art. 69)

- No mandatory obligations
- Commission and Board to encourage drawing up of codes of conduct intended to foster the **voluntary application of requirements to low-risk AI systems**

SCHEMA DI DISEGNO DI LEGGE RECANTE DISPOSIZIONI E DELEGA AL GOVERNO IN MATERIA DI INTELLIGENZA ARTIFICIALE

CAPO I – PRINCIPI E FINALITA'

ART. 1

(Finalità e ambito di applicazione)

L'esecutivo ha sottolineato che **il disegno di legge non si sovrappone al Regolamento europeo sull'intelligenza artificiale** approvato lo scorso 13 marzo dal Parlamento Europeo, di prossima emanazione, **ma ne accompagna il quadro regolatorio** in quegli spazi propri del diritto interno, tenuto conto che il regolamento è impostato su un'architettura di rischi connessi all'uso della intelligenza artificiale (IA).

Le norme intervengono in cinque ambiti:

1. strategia nazionale,
2. autorità nazionali,
3. azioni di promozione,
4. tutela del diritto di autore,
5. sanzioni penali.

1) Principi fondamentali e promozione dell'IA
2) Accessibilità e intelligenza artificiale in ambito sanitario e di disabilità
3) Utilizzo intelligenza artificiale in materia di lavoro
4) Strategia governativa sull'AI
5) Intelligenza artificiale e disciplina penale

SCHEMA DI DISEGNO DI LEGGE RECANTE DISPOSIZIONI E DELEGA AL GOVERNO IN MATERIA DI INTELLIGENZA ARTIFICIALE

CAPO I – PRINCIPI E FINALITA'

ART. 1

(Finalità e ambito di applicazione)

A

2) Accessibilità e intelligenza artificiale in ambito sanitario e di disabilità

L'utilizzo dell'intelligenza artificiale non può in alcun modo selezionare con criteri discriminatori condizionando e restringendo l'accesso alle prestazioni sanitarie.

Prioritario è il diritto dell'interessato ad essere informato circa l'utilizzo di tali tecnologie.

L'utilizzo dei sistemi di IA in ambito sanitario deve lasciare impregiudicata la spettanza della **decisione** alla **professione medica**.

decisione alla **professione medica**.

I **trattamenti di dati**, anche personali, eseguiti da soggetti pubblici e privati senza scopo di lucro per la **ricerca e la sperimentazione scientifica** nella realizzazione di sistemi di intelligenza artificiale per finalità terapeutica e farmacologica, **sono dichiarati di rilevante interesse pubblico**.
Si istituisce una **piattaforma di intelligenza artificiale** per il supporto alle finalità di cura e, in particolare, per l'assistenza territoriale.

Ministero della Salute

Consiglio Superiore di Sanità

Sessione LII (2019-2022)

Presidente: Prof. Franco Locatelli

Sezione V*

Presidente: Prof. Giuseppe Remuzzi
Segretario tecnico: Dr. Franco Abbenda

"I sistemi di intelligenza artificiale come strumento di supporto alla diagnostica"

Coordinatore: Prof. A. Laghi

a) le decisioni basate-su-algoritmi (*algorithm-based decisions*): sono decisioni integralmente umane, anche se basate in tutto o in parte su informazioni ottenute mediante calcoli algoritmici;

b) le decisioni guidate-da-algoritmi (*algorithm-driven decisions*): queste decisioni sono ancora prevalentemente umane, ma in termini molto ristretti rispetto a quanto determinato dall'esito delle procedure informatiche;

c) le decisioni determinate-da-algoritmi (*algorithm-determined decisions*): sono gli esiti dei processi digitali ad assumere le decisioni, senza alcun intervenuto umano»[124].

4.3 Le implicazioni nella relazione medico-paziente. Il consenso informato

La particolare caratterizzazione del tipo di sistema, per come sopra differenziato, reca con sé comprensibili tratti di differenziazione in ordine alle varie problematiche che concernono l'àmbito sanitario, a partire dalla incidenza nella relazione tra il medico e il paziente. Quest'ultima, infatti, si connota tradizionalmente, e trova oggi pieno riconoscimento a livello normativo all'art. 1, comma 2 legge 22 dicembre 2017, n. 219, recante norme in materia di consenso informato e di disposizioni anticipate di trattamento, quale rapporto che traduce per l'appunto una dimensione essenzialmente

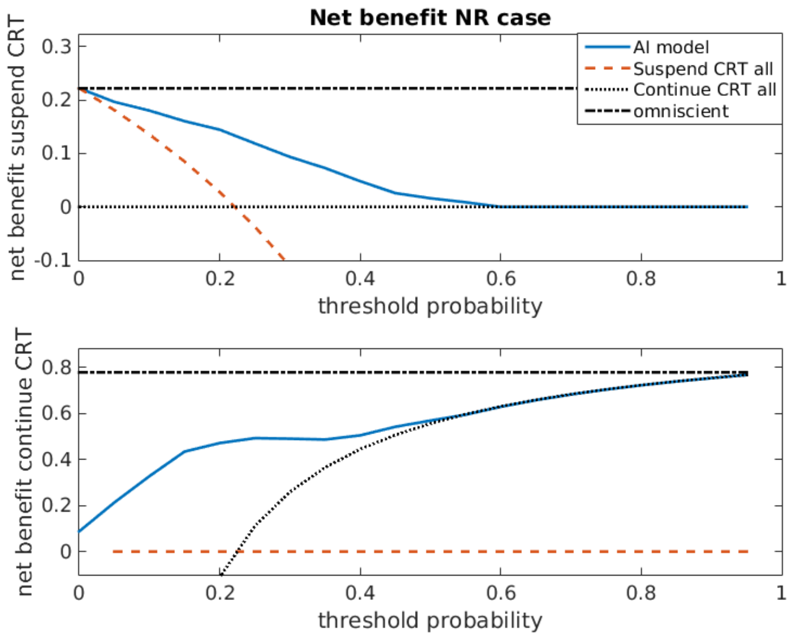
PRINCIPI ETICI

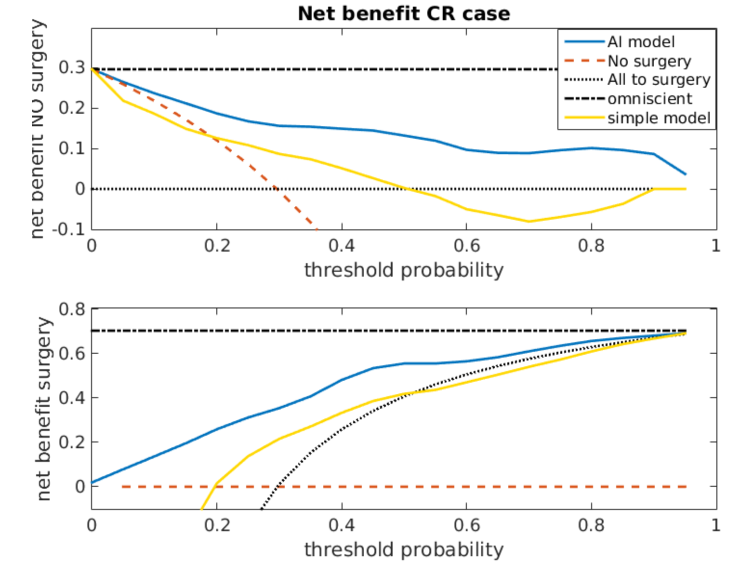
MODELLO DI INTELLIGENZA ARTIFICIALE CHE GESTISCA L'ENORME MOLE DI INFORMAZIONI NUMERICHE ESTRATTE DALLA TEXTURE CREANDO CURVE DI DECISIONE E VALUTAZIONI PROGNOSTICHE

Research article

MR-based artificial intelligence model to assess response to therapy in locally advanced rectal cancer

R. Ferrari[a], C. Mancini-Terracciano[b], C. Voena[b,*], M. Rengo[c], M. Zerunian[c], A. Ciardiello[b,d], S. Grasso[d], V. Mare[d,e], R. Paramatti[b,d], A. Russomando[f], R. Santacesaria[b], A. Satta[g], E. Solfaroli Camillocci[b,d,h], R. Faccini[b,d], A. Laghi[i]

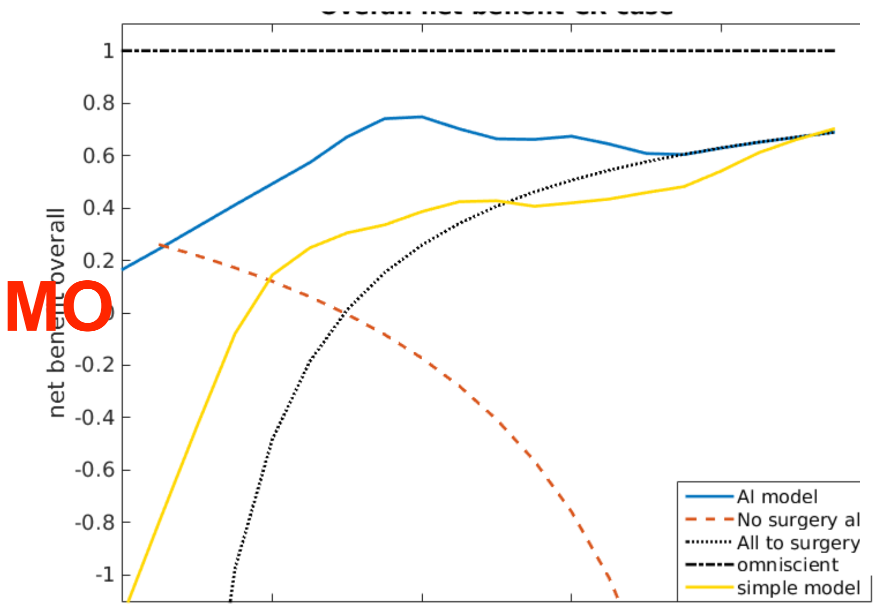


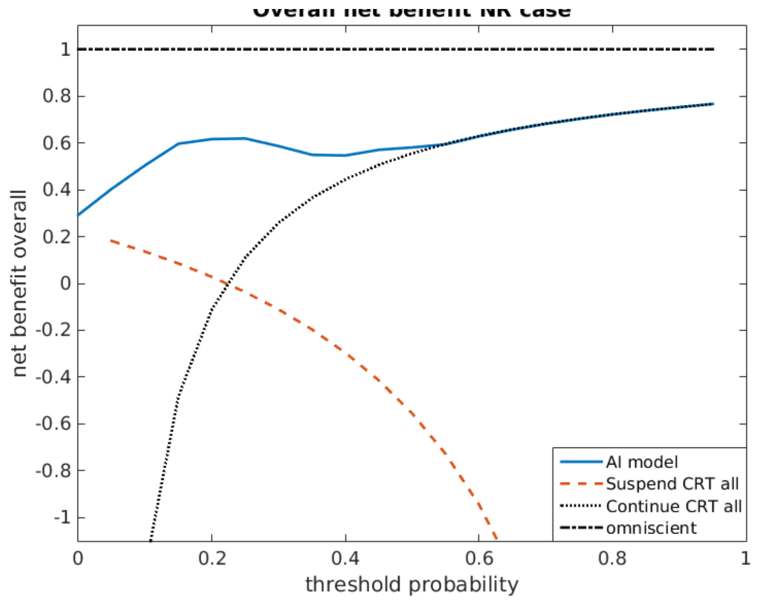


ETICA ED AI UNA QUESTIONE ATTUALE

INTERAZIONI UOMO MACCHINA QUANDO

LE AUTOMAZIONI SARANNO OLTRE IL CONTROLLO DELL'UOMO





Published OnlineFirst September 5, 2017; DOI: 10.1158/1078-0432.CCR-17-1510

Personalized Medicine and Imaging

Clinical Cancer Research

A Radiomics Nomogram for the Preoperative Prediction of Lymph Node Metastasis in Bladder Cancer

Shaoxu Wu[1,2], Junjiong Zheng[1,2], Yong Li[3], Hao Yu[1,2], Siya Shi[3], Weibin Xie[1,2], Hao Liu[1,2], Yangfan Su[1,2], Jian Huang[1,2], and Tianxin Lin[1,2]

PNAS

CrossMark

PNAS PLUS

Automatic classification of prostate cancer Gleason scores from multiparametric magnetic resonance images

Duc Fehr[a,1], Harini Veeraraghavan[a,1,2], Andreas Wibmer[b], Tatsuo Gondo[c], Kazuhiro Matsumoto[c], Herbert Alberto Vargas[b], Evis Sala[b], Hedvig Hricak[b], and Joseph O. Deasy[a]

ASPETTI ETICI

Chi ha la responsabilità civile dell’intelligenza artificiale?

- Il sistema intelligente potrebbe sbagliare (sistemi predittivi in ambito bancario che provocano minicrisi)

- Dalla decisione può derivare un danno (macchina a guida autonoma se un pedone passa con il rosso che deve fare tutelare l’incolumità del guidatore o del pedone???)

https://www.moralmachine.net/

LIVELLI DI AUTOMATIZZAZIONE

Livello 0 – nessuna autonomia:
il conducente si deve occupare di ogni singolo aspetto della guida del veicolo.

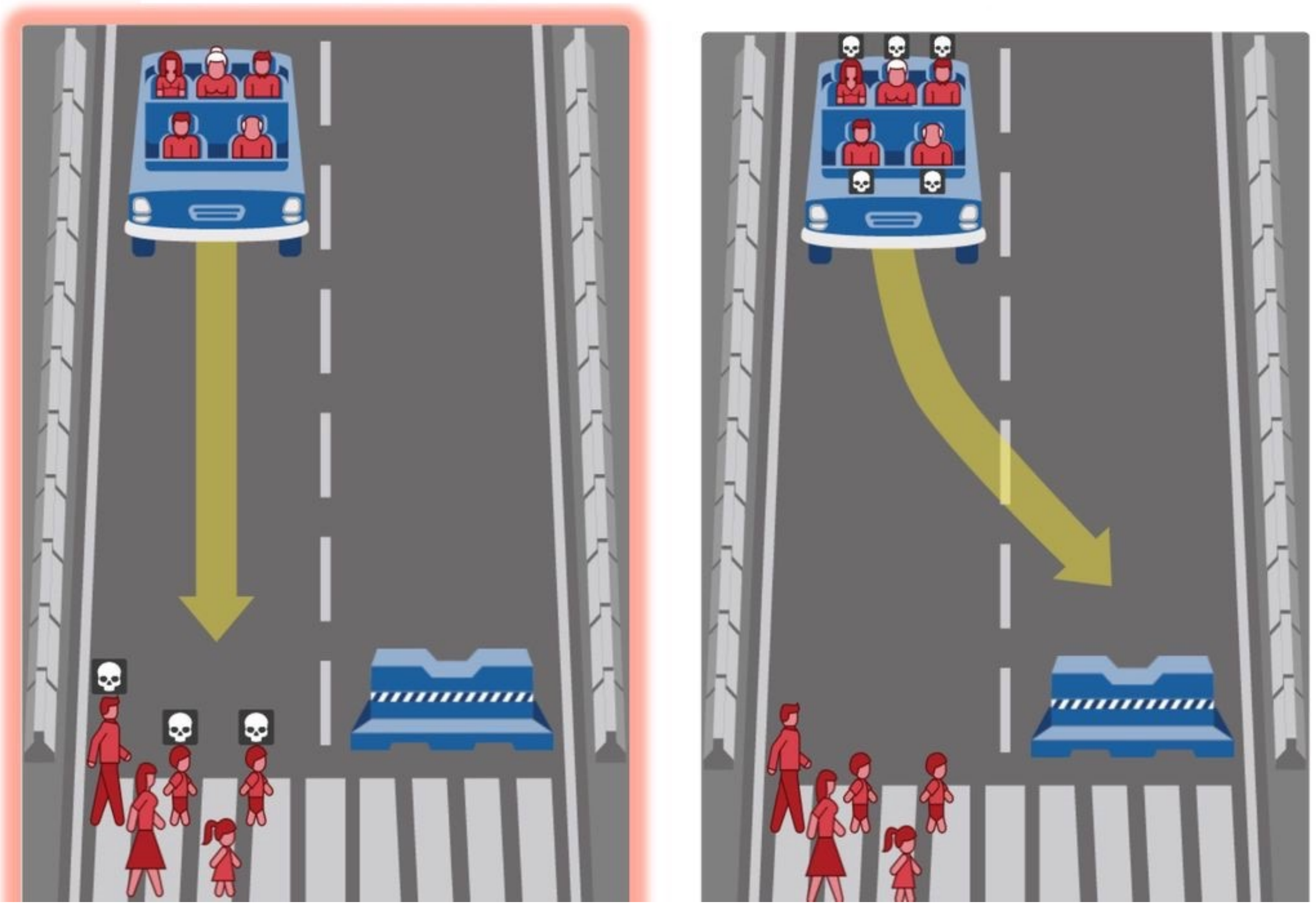
Livello 1 – assistenza alla guida:
l’automobile regola la velocità (Tempomat) oppure è equipaggiata con un sistema di assistenza al mantenimento della corsia; il conducente si deve occupare di ogni ulteriore aspetto della guida. Il conducente deve sorvegliare tutto e, se necessario, riprendere il controllo del mezzo.

Livello 2 – automazione parziale:
per determinati lassi di tempo o in determinate situazioni (ad es. durante i sorpassi in autostrada), l’auto sterza e regola la velocità, autonomamente. Il conducente, però, deve sempre essere pronto a riprendere i comandi del veicolo.

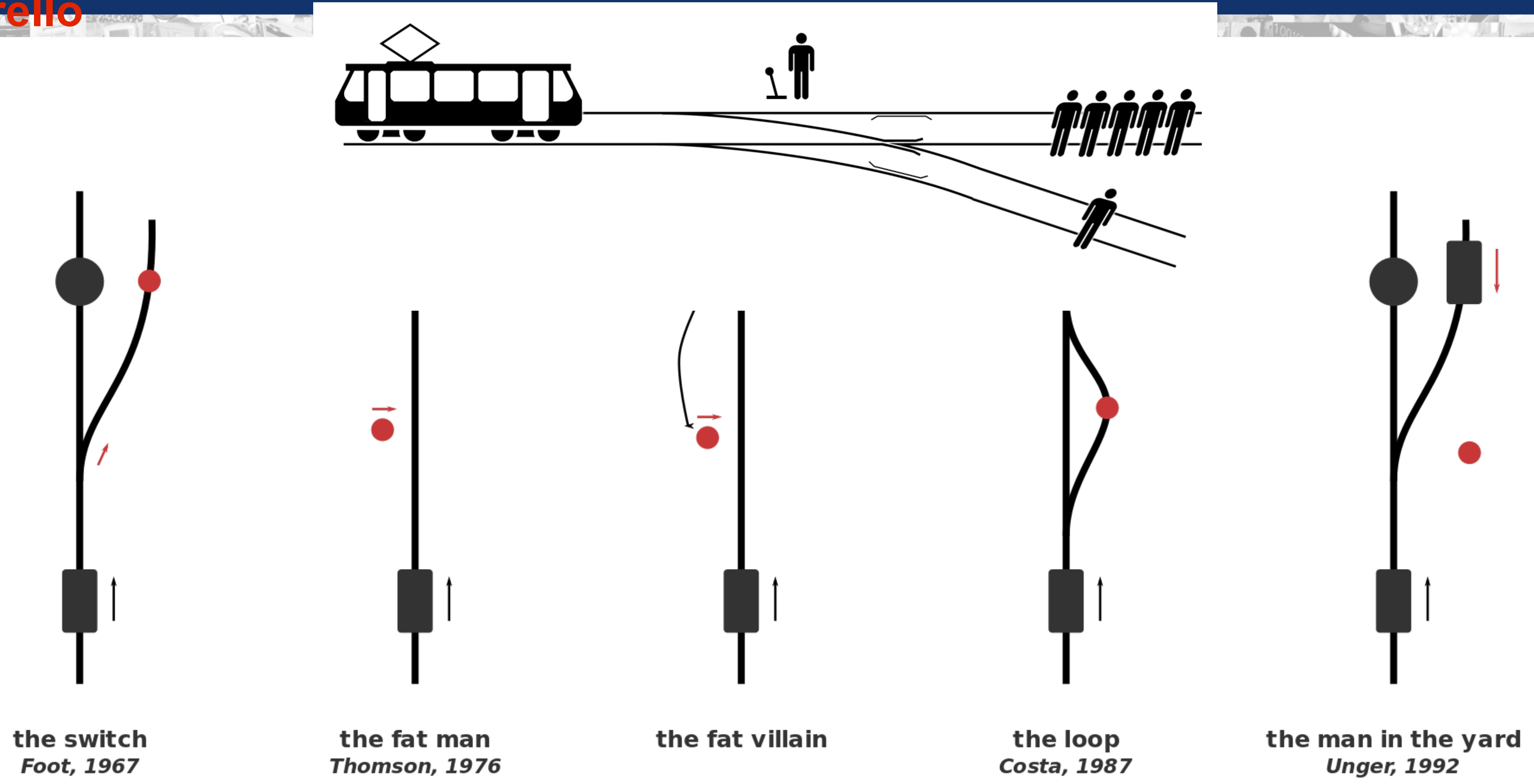
Livello 3 – automazione condizionata:
anche nel terzo livello, accelerazione/frenata e comandi direzionali (sterzo) sono lasciati al veicolo. Tuttavia, sebbene il conducente non sia tenuto a monitorare di continuo il sistema, deve essere in grado di riprendere i comandi in caso di richiesta del sistema (ad es. in caso di nebbia).

Livello 4 – elevata automazione:
l’automobile assume completamente e svolge autonomamente determinate applicazioni (ad es. guida in autostrada). Soltanto alla fine dell’applicazione (ad es. all’uscita autostradale) il conducente deve riprendere i comandi dell’auto.

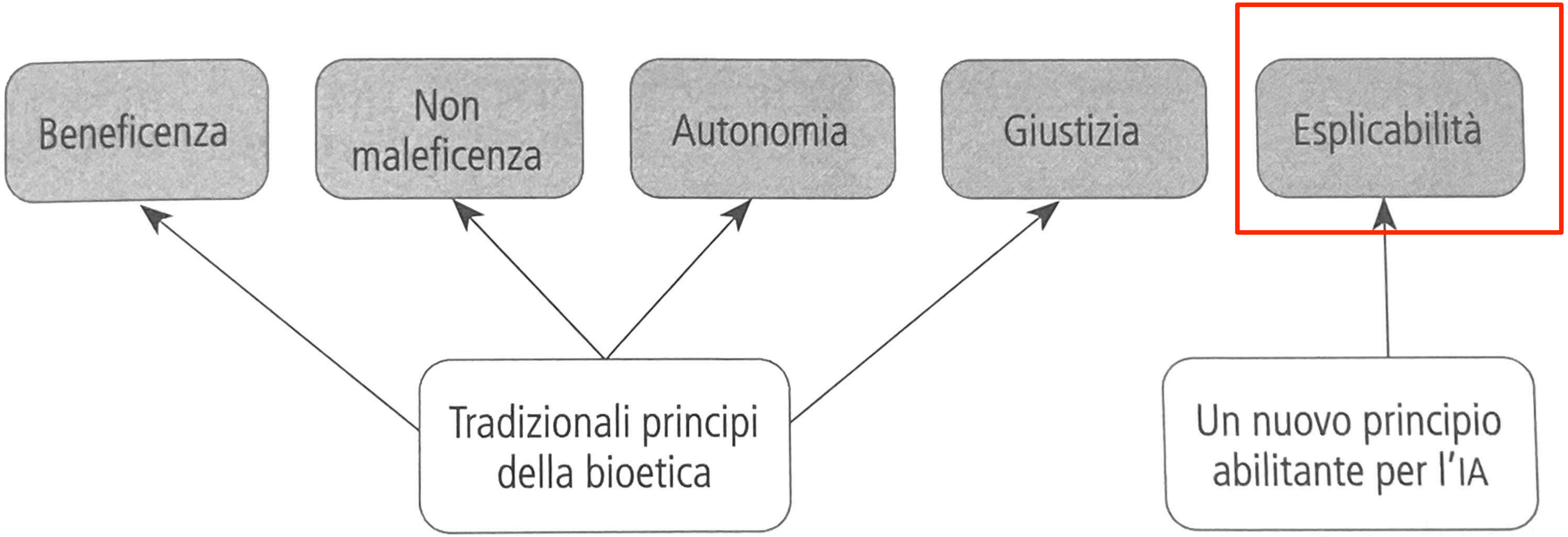
Livello 5 – completa automazione:
il sistema rileva tutti i compiti, dalla partenza all’arrivo a destinazione. Il conducente non è più necessario, a prescindere se nevichi, piova, ci sia nebbia o un cantiere che restringe la carreggiata.



il dilemma del carrello



Nel 2001 il neuroscienziato e filosofo Joshua Greene di Harvard, avendo constatato che la maggior parte delle persone considera una scelta morale deviare il carrello verso una sola persona, mentre spingere una persona sulle rotaie un omicidio, tramite scansione cerebrale ha constatato che nelle due situazioni si attivano aree cerebrali distinte, e ha chiamato le due situazioni decisione morale impersonale e decisione morale personale.


Beneficenza
Non maleficenza
Autonomia
Giustizia
Esplicabilità
Tradizionali principi della bioetica
Un nuovo principio abilitante per l'IA


Luciano Floridi
Etica dell'intelligenza artificiale
Sviluppi, opportunità, sfide
Raffaello Cortina Editore
Scienza e Idee

ESPLICABILITA': IL PROBLEMA DELLA BLACK BOX

ARTICLES
https://doi.org/10.1038/s42256-021-00338-7
nature machine intelligence
Check for updates

AI for radiographic COVID-19 detection selects shortcuts over signal

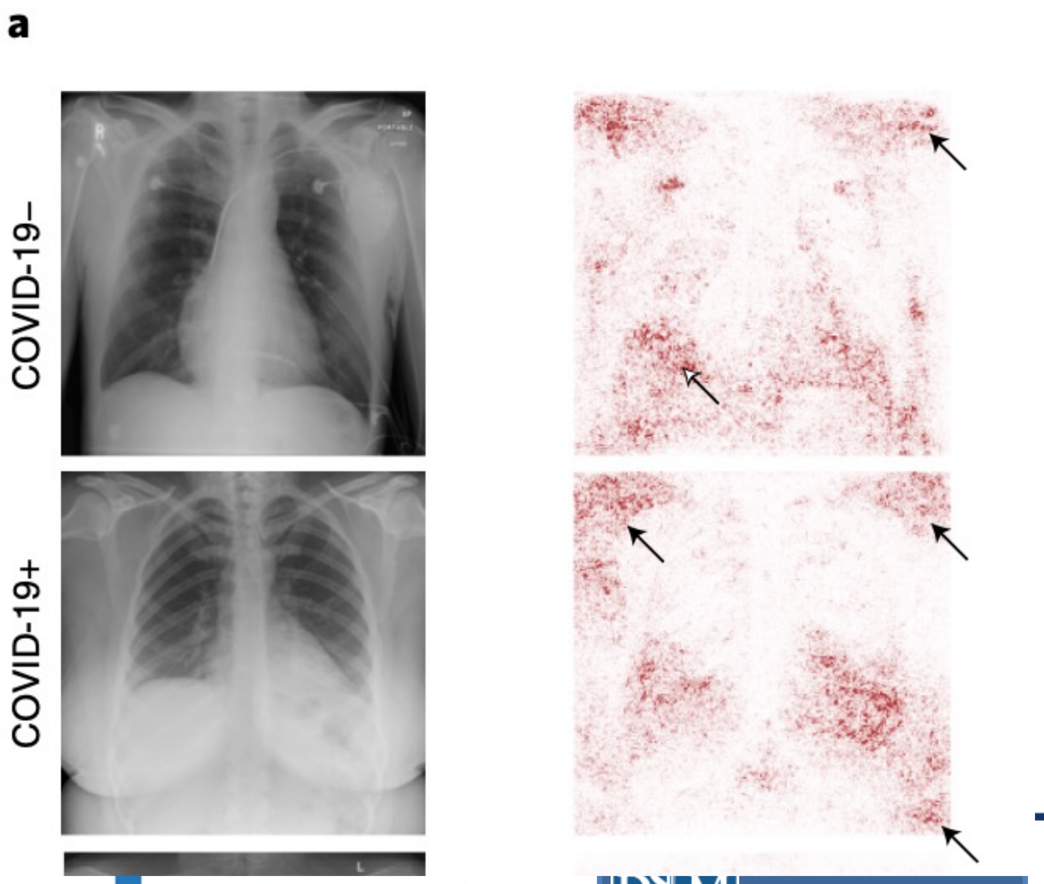
Alex J. DeGrave[1,2,3], Joseph D. Janizek[1,2,3] and Su-In Lee[1]✉

Il sistema aveva avuto un addestramento con immagini radiografiche da diversi siti che presentavano lettere R o L diverse nei vari ospedali

Il sistema ha correlato una particolare forma della lettera con la possibilità di avere il covid non basandosi più sulla immagine radiografica ma sulla posizione e morfologia della lettera

Questo è il tipico problema del black box

La soluzione è stata mostrare delle mappe che riporta quale parte dell'immagine il sistema utilizza per la diagnosi



What does explainable AI mean?

- *Interpretability,* refers to the understanding of the output of the algorithm for end-user implementation
- *Explainability*, involves clarifying how a decision was reached so that a broader range of users can understand it.
- *Transparency*, refers to the degree of the incomprehensibility of the model.
- *Justifiability*, involves providing an in-depth case to support certain conclusions.
- *Contestability*, relates to the fact that users are able to proclaim a particular decision.

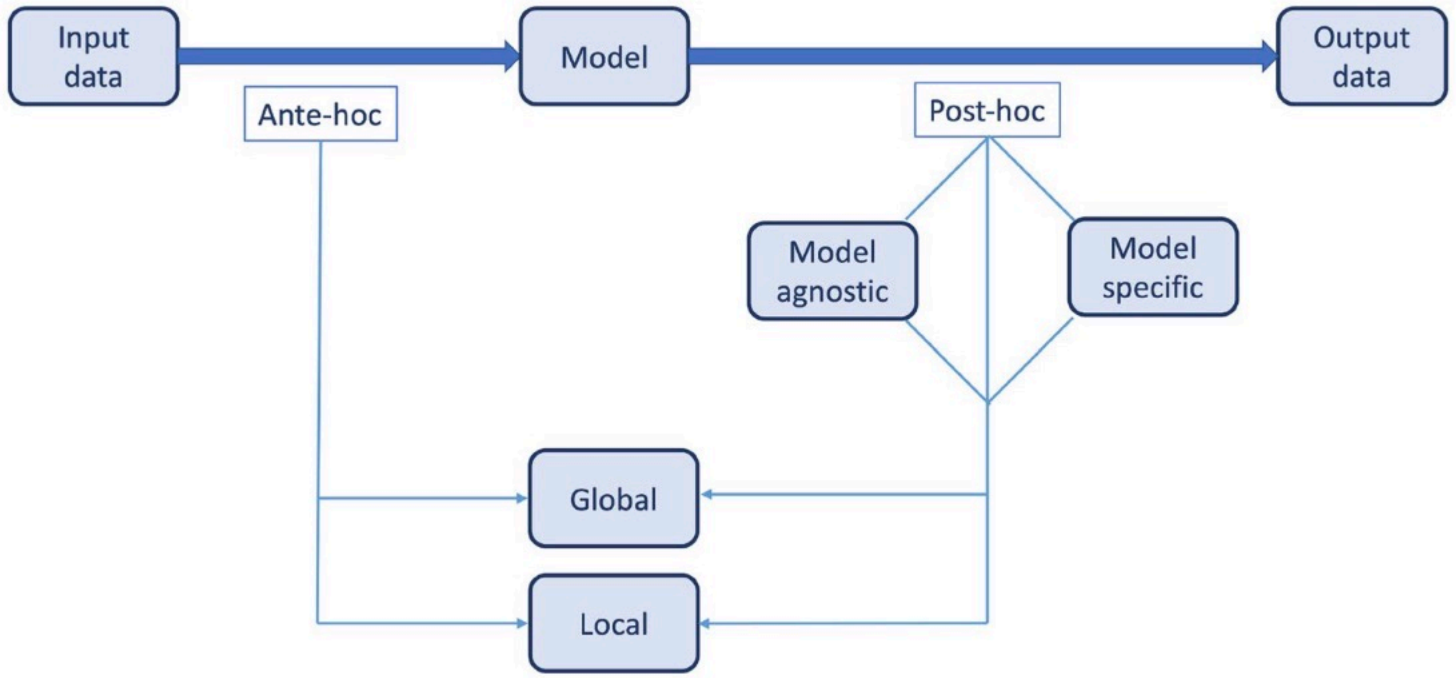
La radiologia medica (2023) 128:755–764
https://doi.org/10.1007/s11547-023-01634-5

COMPUTER APPLICATION

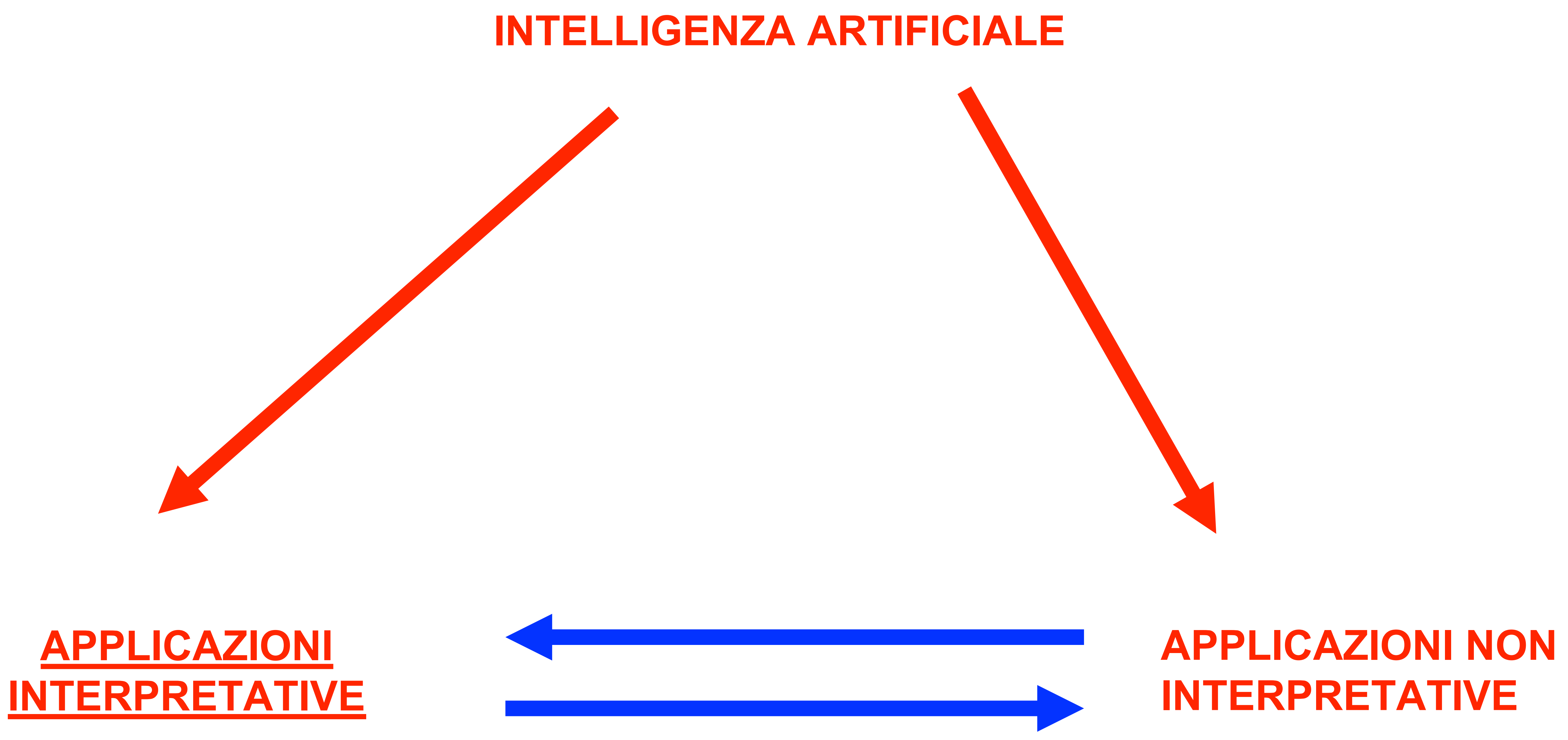
Explainable AI in radiology: a white paper of the Italian Society of Medical and Interventional Radiology

Emanuele Neri[1] · Gayane Aghakhanyan[1] · Marta Zerunian[2] · Nicoletta Gandolfo[3] · Roberto Grassi[4] · Vittorio Miele[5] · Andrea Giovagnoni[6] · Andrea Laghi[2] · SIRM expert group on Artificial Intelligence

Received: 17 February 2023 / Accepted: 19 April 2023 / Published online: 8 May 2023



PRINCIPALI APPLICAZIONI AI

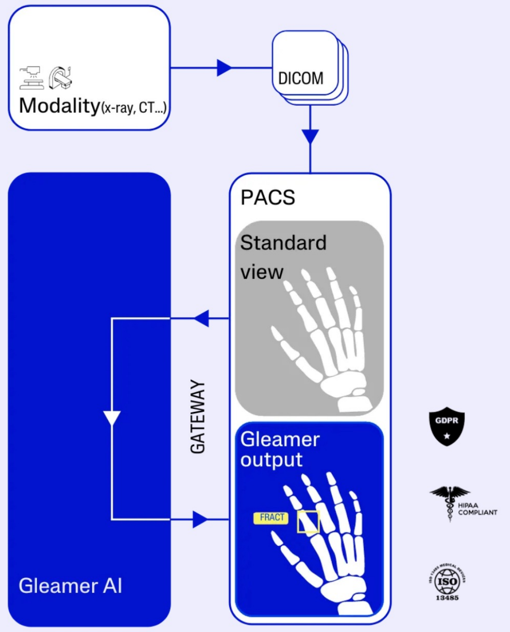

INTELLIGENZA ARTIFICIALE
APPLICAZIONI INTERPRETATIVE
APPLICAZIONI NON INTERPRETATIVE

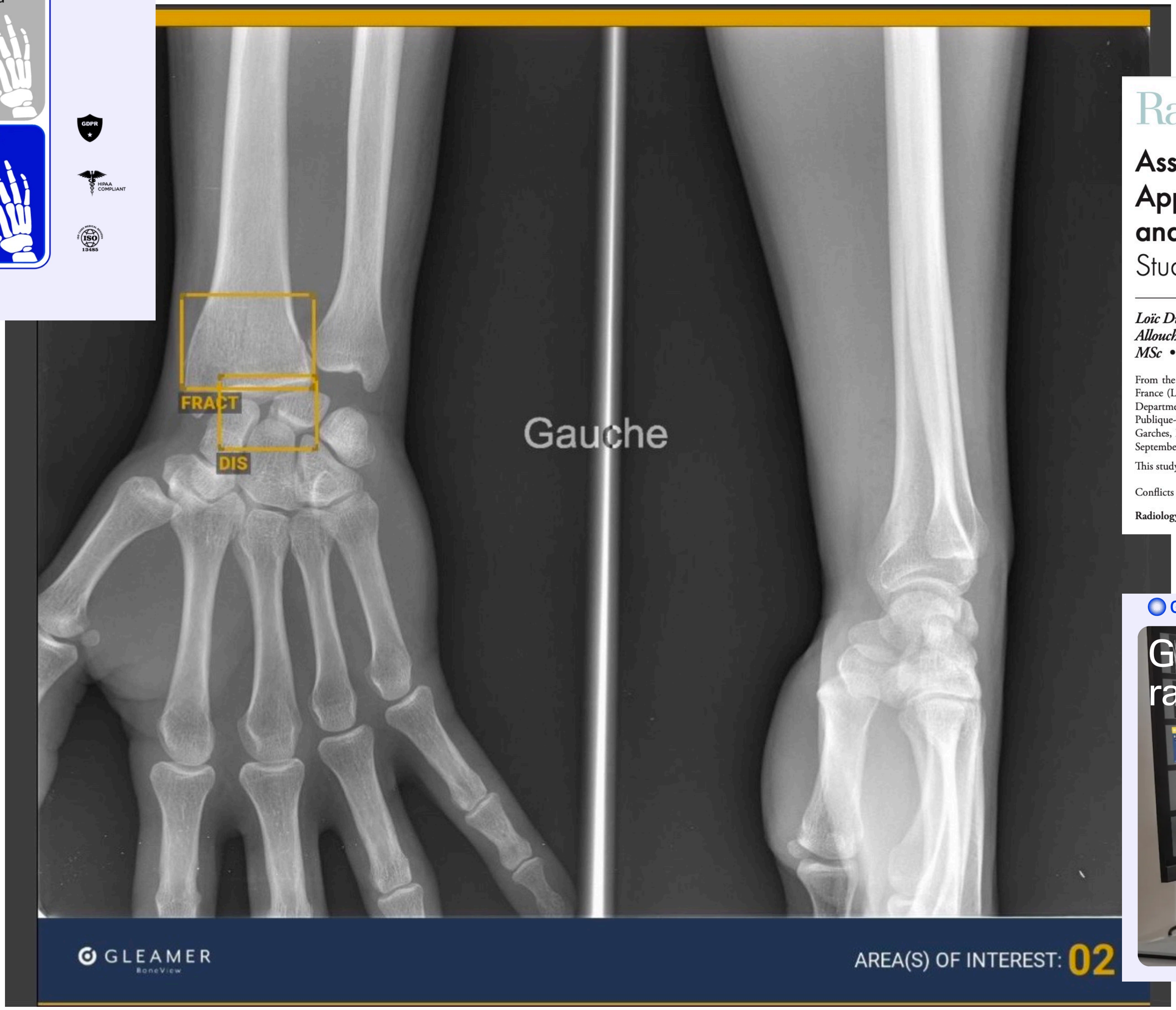
SOFTWARE AI DISPONIBILI

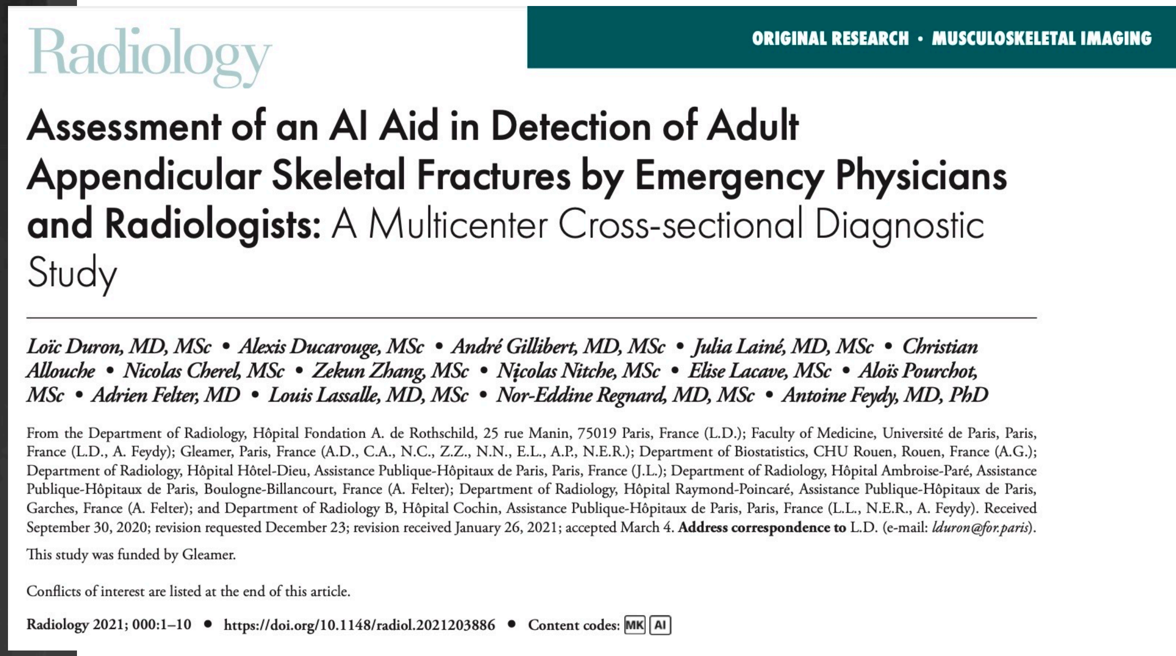
DETECTION

Integrates seamlessly into your existing workflow

Our solutions adhere to the strictest standards for patient data security. Additionally, we prioritize seamless integration into your existing workflow, ensuring transparency and eliminating the need for additional tools or software.






Radiology

ORIGINAL RESEARCH • MUSCULOSKELETAL IMAGING

Assessment of an AI Aid in Detection of Adult Appendicular Skeletal Fractures by Emergency Physicians and Radiologists: A Multicenter Cross-sectional Diagnostic Study

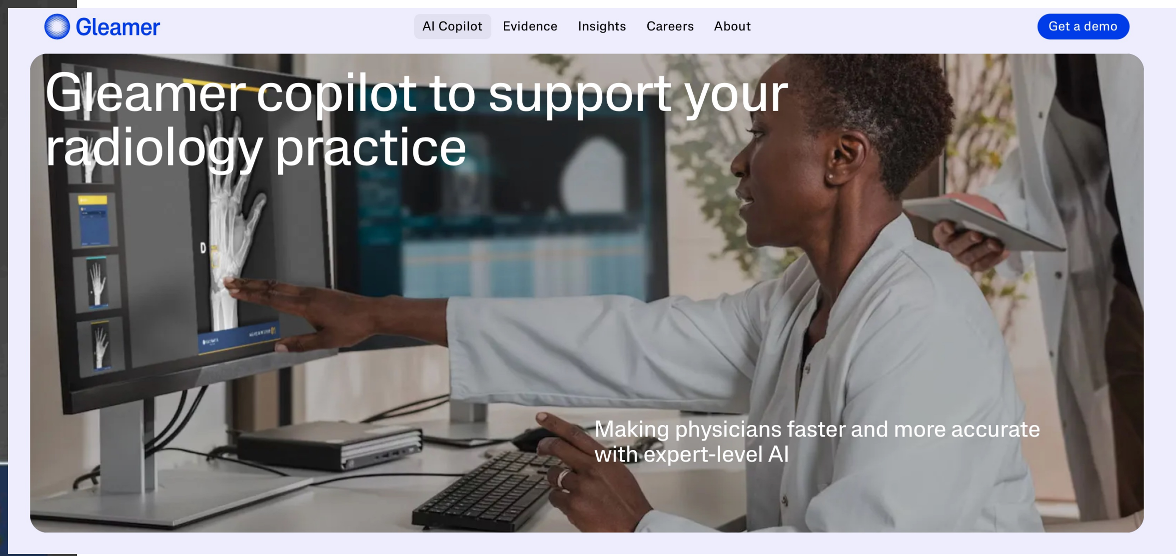
Loïc Duron, MD, MSc • Alexis Ducarouge, MSc • André Gillibert, MD, MSc • Julia Lainé, MD, MSc • Christian Allouche • Nicolas Cherel, MSc • Zekun Zhang, MSc • Nicolas Nitche, MSc • Elise Lacave, MSc • Aloïs Pourchot, MSc • Adrien Felter, MD • Louis Lassalle, MD, MSc • Nor-Eddine Regnard, MD, MSc • Antoine Feydy, MD, PhD

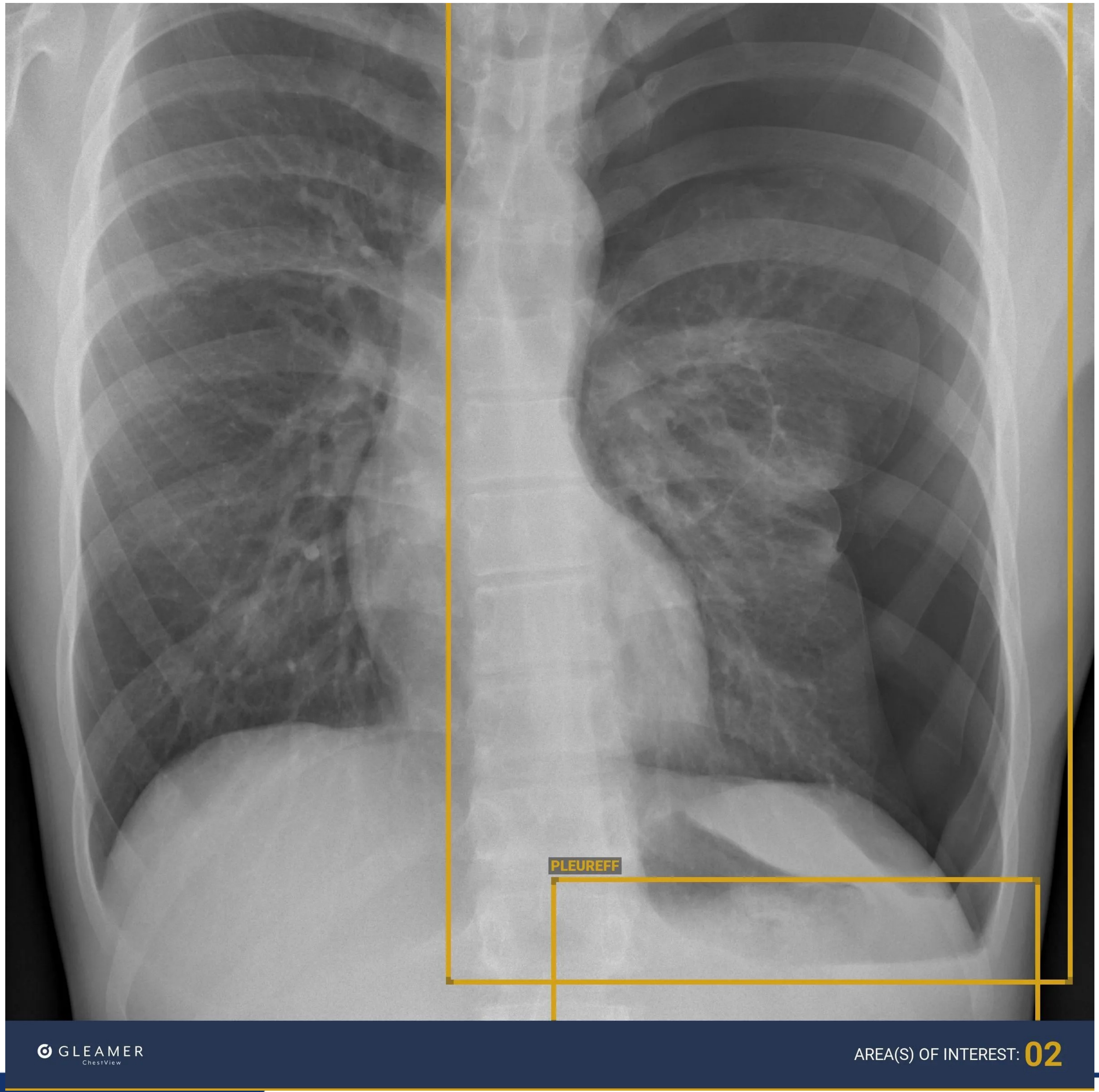
From the Department of Radiology, Hôpital Fondation A. de Rothschild, 25 rue Manin, 75019 Paris, France (L.D.); Faculty of Medicine, Université de Paris, Paris, France (L.D., A. Feydy); Gleamer, Paris, France (A.D., C.A., N.C., Z.Z., N.N., E.L., A.P., N.E.R.); Department of Biostatistics, CHU Rouen, Rouen, France (A.G.); Department of Radiology, Hôpital Hôtel-Dieu, Assistance Publique-Hôpitaux de Paris, Paris, France (J.L.); Department of Radiology, Hôpital Ambroise-Paré, Assistance Publique-Hôpitaux de Paris, Boulogne-Billancourt, France (A. Felter); Department of Radiology, Hôpital Raymond-Poincaré, Assistance Publique-Hôpitaux de Paris, Garches, France (A. Felter); and Department of Radiology B, Hôpital Cochin, Assistance Publique-Hôpitaux de Paris, Paris, France (L.L., N.E.R., A. Feydy). Received September 30, 2020; revision requested December 23; revision received January 26, 2021; accepted March 4. **Address correspondence to** L.D. (e-mail: *lduron@for.paris*).

This study was funded by Gleamer.

Conflicts of interest are listed at the end of this article.

Radiology 2021; 000:1–10 • https://doi.org/10.1148/radiol.2021203886 • Content codes: MK AI





Radiology

ORIGINAL RESEARCH • THORACIC IMAGING

Using AI to Improve Radiologist Performance in Detection of Abnormalities on Chest Radiographs

Souhail Bennani, MD • Nor-Eddine Regnard, MD • Jeanne Ventre, PhD • Louis Lassalle, MD • Toan Nguyen, MD • Alexis Ducarouge, MSc • Lucas Dargent, MD • Enora Guillo, MD • Elodie Gouhier, MD • Sophie-Hélène Zaimi, MD • Emma Canniff, MD • Cécile Malandrin, MD • Philippe Khafagy, MD • Hasmik Koulakian, MD • Marie-Pierre Revel, MD, PhD • Guillaume Chassagnon, MD, PhD

From the Department of Thoracic Imaging, Cochin Hospital, AP-HP, 27 Rue du Faubourg Saint-Jacques, Paris 75014, France (S.B., L.D., E. Guillo, E. Gouhier, S.H.Z., E.C., M.P.R., G.C.); Gleamer, Paris, France (S.B., N.E.R., J.V., L.L., T.N., A.D.); Réseau d'Imagerie Sud Francilien, Lieusant, France (N.E.R., L.L., C.M.); Department of Pediatric Radiology, Armand Trousseau Hospital, AP-HP, Paris, France (T.N.); HFR Fribourg, Fribourg, Switzerland (P.K.); and Centre d'Imagerie Médicale de l'Ouest Parisien, Paris, France (H.K.). Received April 20, 2023; revision requested June 26; revision received October 9; accepted October 23. **Address correspondence to** M.P.R. (email: *marie-pierre.revel@aphp.fr*).

Supported by Gleamer.

Conflicts of interest are listed at the end of this article.

Radiology 2023; 309(3):e230860 • https://doi.org/10.1148/radiol.230860 • Content codes: CH AI

RAPIDAI

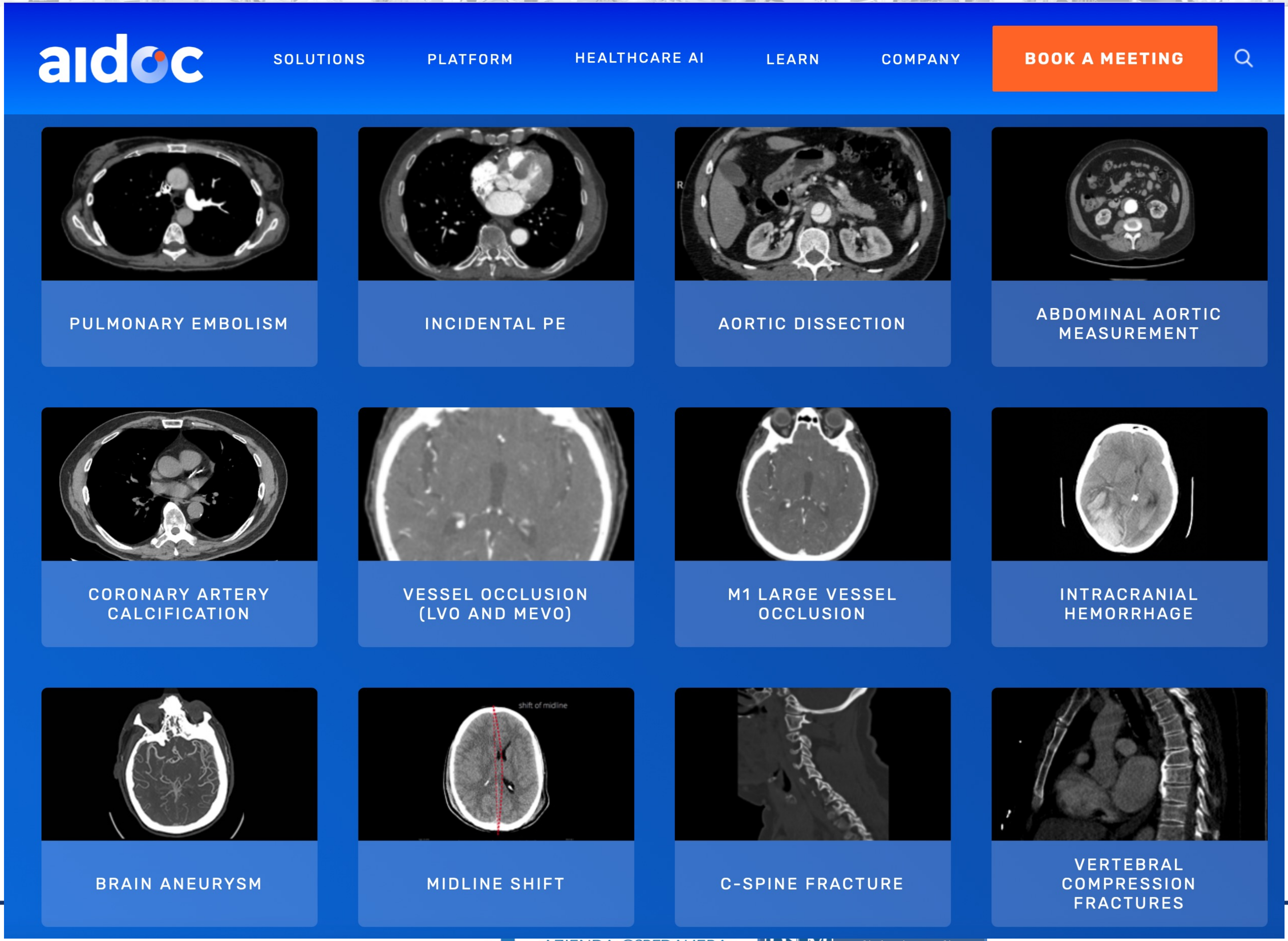
Products & Solutions   Company   Services & Training   Resources   News & Events

RapidAI › Why RapidAI for Stroke › Rapid CTP

Rapid CTP

Advanced CT Perfusion Analysis in Minutes

Rapid CTP is the only clinically validated software with an FDA indication to aid in the selection of patients for acute stroke therapy.

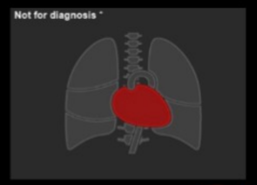

aidoc
SOLUTIONS
PLATFORM
HEALTHCARE AI
LEARN
COMPANY
BOOK A MEETING
PULMONARY EMBOLISM
INCIDENTAL PE
AORTIC DISSECTION
ABDOMINAL AORTIC MEASUREMENT
CORONARY ARTERY CALCIFICATION
VESSEL OCCLUSION (LVO AND MEVO)
M1 LARGE VESSEL OCCLUSION
INTRACRANIAL HEMORRHAGE
BRAIN ANEURYSM
shift of midline
MIDLINE SHIFT
C-SPINE FRACTURE
VERTEBRAL COMPRESSION FRACTURES

Quantitative results as added-value
The AI-Rad Companion Chest CT in clinical routine

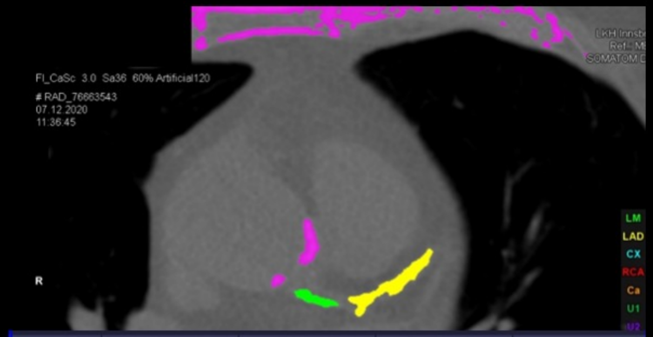
SIEMENS Healthineers

Case 2

AI-Rad Companion outcome:
Automated detection and quantification of coronary calcifications and automated exclusion of existing stent graft.



HEART	
Heart volume	1112.7 ml
Total Coronary Calcium Volume	1453.4 mm³
Calcium Range *	IV



Artery	Lesions	Volume / mm³	Equiv. Mass / mg	Score
LM	1	169,4	49,40	218,5
LAD	7	922,6	272,45	1161,6
CX	3	[illegible]	87,16	443,6
RCA	0	0,0	0,00	0,0
Ca	0	0,0	0,00	0,0
Total	11	1456,5	409,01	1823,6
U1	0	0,0	0,00	0,0
U2	0	0,0	0,00	0,0

Settings
Score Type: User defined, Threshold: 130 HU (105,3 mg/cm³ CaHA)
Mass calibration factor: 0,81

Postprocessing on *syngo*.via shows comparable results

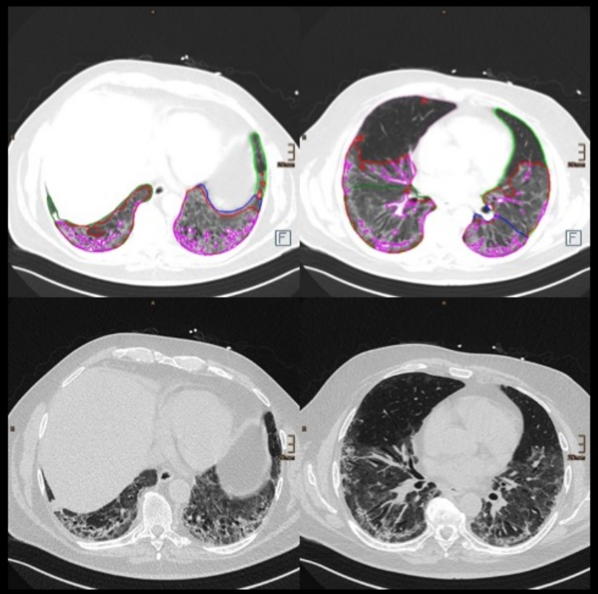
Courtesy of Department of Radiology, Medical University of Innsbruck - Tirol Kliniken, Innsbruck, Austria.

Digital & Automation

Quantitative results as added-value
The AI-Rad Companion Chest CT in clinical routine

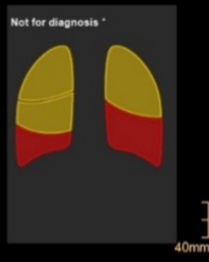
SIEMENS Healthineers

Case 1: Examination date 29.04.2020



Results
Pulmonary Density
AI-Rad Companion

LUNG OPACITY	Both Lungs	Right Lung	Left Lung
Opacity Score	14	8	6
Total Volume [ml]	3577.96	1990.42	1587.55
Opacity Volume [ml]	1894.37	947.34	947.03
Opacity Percentage [%]	52.95	47.60	59.65
High Opacity Volume [ml]	124.70	59.88	64.83
High Opacity Percentage [%]	3.49	3.01	4.08
Mean HU Total [HU]	-677.20	-688.70	-662.79
Mean HU of Opacity [HU]	-580.13	-583.35	-576.92
Standard Deviation Total [HU]	219.27	218.18	219.78
Standard Deviation of Opacity [HU]	202.58	201.18	203.93



LUNG LOBE OPACITY	Right Upper	Right Middle	Right Lower	Left Upper	Left Lower
Opacity Score	2	2	4	2	4
Total Volume [ml]	797.09	515.02	678.31	1084.95	502.60
Opacity Volume [ml]	226.95	134.95	585.44	482.79	464.24
Opacity Percentage [%]	28.47	26.20	86.31	44.50	92.37
High Opacity Volume [ml]	5.88	3.87	50.14	19.29	45.53
High Opacity Percentage [%]	0.74	0.75	7.39	1.78	9.06
Mean HU Total [HU]	-750.86	-771.75	-552.60	-730.83	-515.90
Mean HU of Opacity [HU]	-616.98	-643.02	-556.55	-634.73	-516.79
Standard Deviation Total [HU]	179.41	180.30	221.07	186.87	213.59
Standard Deviation of Opacity [HU]	168.61	168.49	214.36	180.15	209.75

* Colors are based on institutional settings.
They are not an indication or recommendation for treatment.
To interpret the results, please refer to the user documentation.

Courtesy of Department of Radiology, Medical University of Innsbruck - Tirol Kliniken, Innsbruck, Austria.

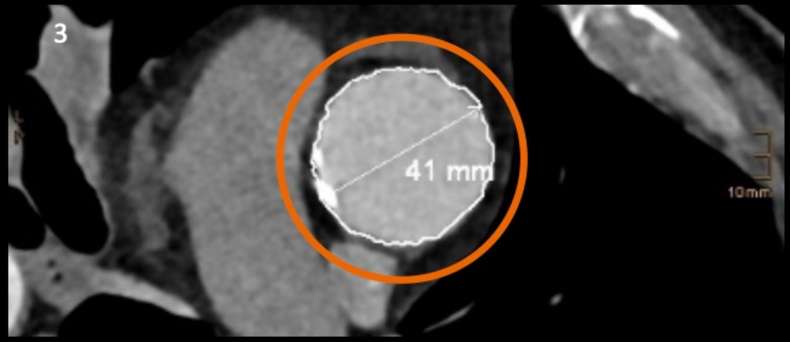
Digital & Automation

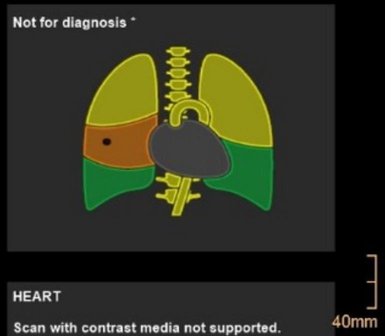
Quantitative results as added-value
The AI-Rad Companion Chest CT in clinical routine

SIEMENS Healthineers

Case 2

AI-Rad Companion outcome:
Automated detection and quantification of thoracic aorta. The actual diameter of position #3 exceeds the defined threshold and is marked in the result overview.





HEART
Scan with contrast media not supported.

AORTA	Diameter [mm]		Diameter [mm]
1 Sin. of Vals	37	6 Prox. Desc.	30
2 Sinot. Jnct.	[illegible]	7 Mid Desc.	29
3 Mid Asc.	41	8 At Diaphr.	27
4 Prox. Arch	36	9 Abd. Aorta	27
5 Mid Arch	32		
Aorta Range *			II

Courtesy of Department of Radiology, Medical University of Innsbruck - Tirol Kliniken, Innsbruck, Austria.

Digital & Automation

PRIORIZZAZIONE DELLA LISTA DI LAVORO

AI Result	Patient ID	Name	Surname	Description	Date
POSITIVE	400-608-4467	Johnston	Lucinda	Left ankle	Thursday 08-10-2019 10h34 AM
POSITIVE	401-612-1256	Lewis	Smith	Pelvis	Thursday 08-10-2019 10h12 AM
DOUBT	407-003-9332	Dominic	Watts	Right Hand	Thursday 08-10-2019 10h01 AM
DOUBT	512-724-5758	Nicolas	Hamilton	Left Foot	Thursday 08-10-2019 09h52AM
NEGATIVE	008-392-2699	Eli	Coo k	Spine	Thursday 08-10-2019 09h34 AM
NEGATIVE	402-458-0003	Jason	Francis	Rib Cage	Thursday 08-10-2019 09h05 AM

RADIOMICA

Imaging quantitativo (radiomica) necessita di misurazioni accurate dei biomarker estraibili dalle immagini come indicatori di malattia tramite processi di texture analisi.

Le misurazioni e valutazioni dei risultati ottenuti necessitano di processi di automazione molto complessi che solo l'IA ci fornisce


Radiology

Radiomics: Images Are More than Pictures, They Are Data[1]

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Hedvig Hricak, MD, PhD, Dr(hc)

In the past decade, the field of medical image analysis has grown exponentially, with an increased number of pattern recognition tools and an increase in data set sizes. These advances have facilitated the development of processes for high-throughput extraction of quantitative features that

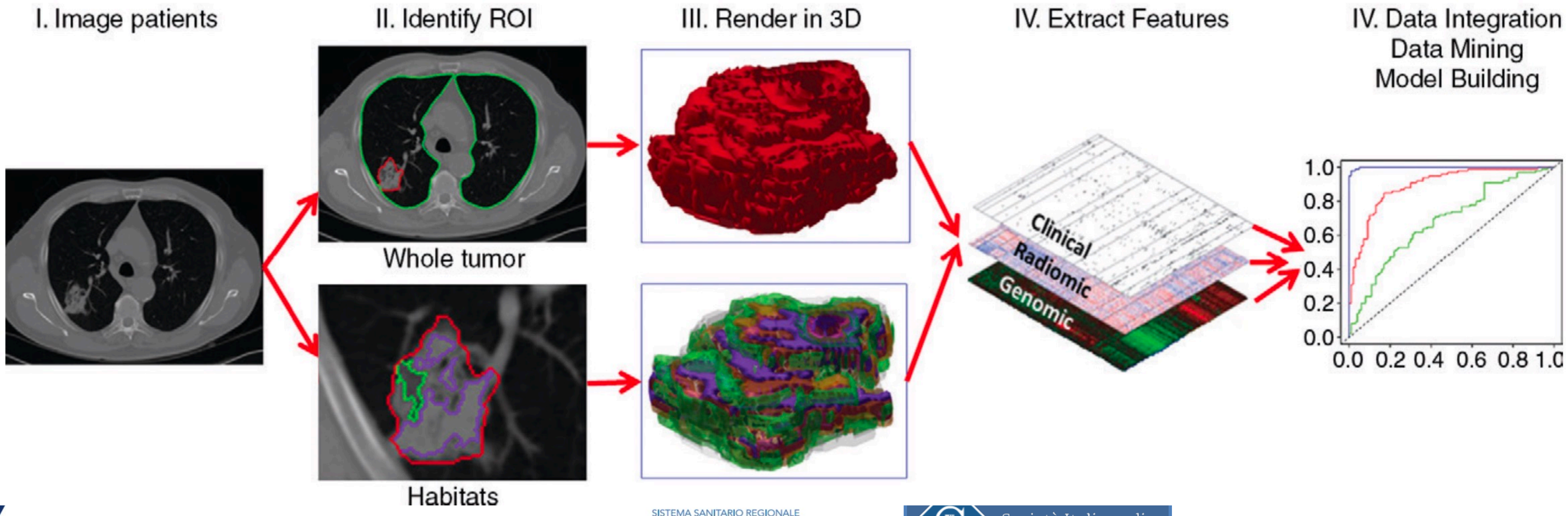
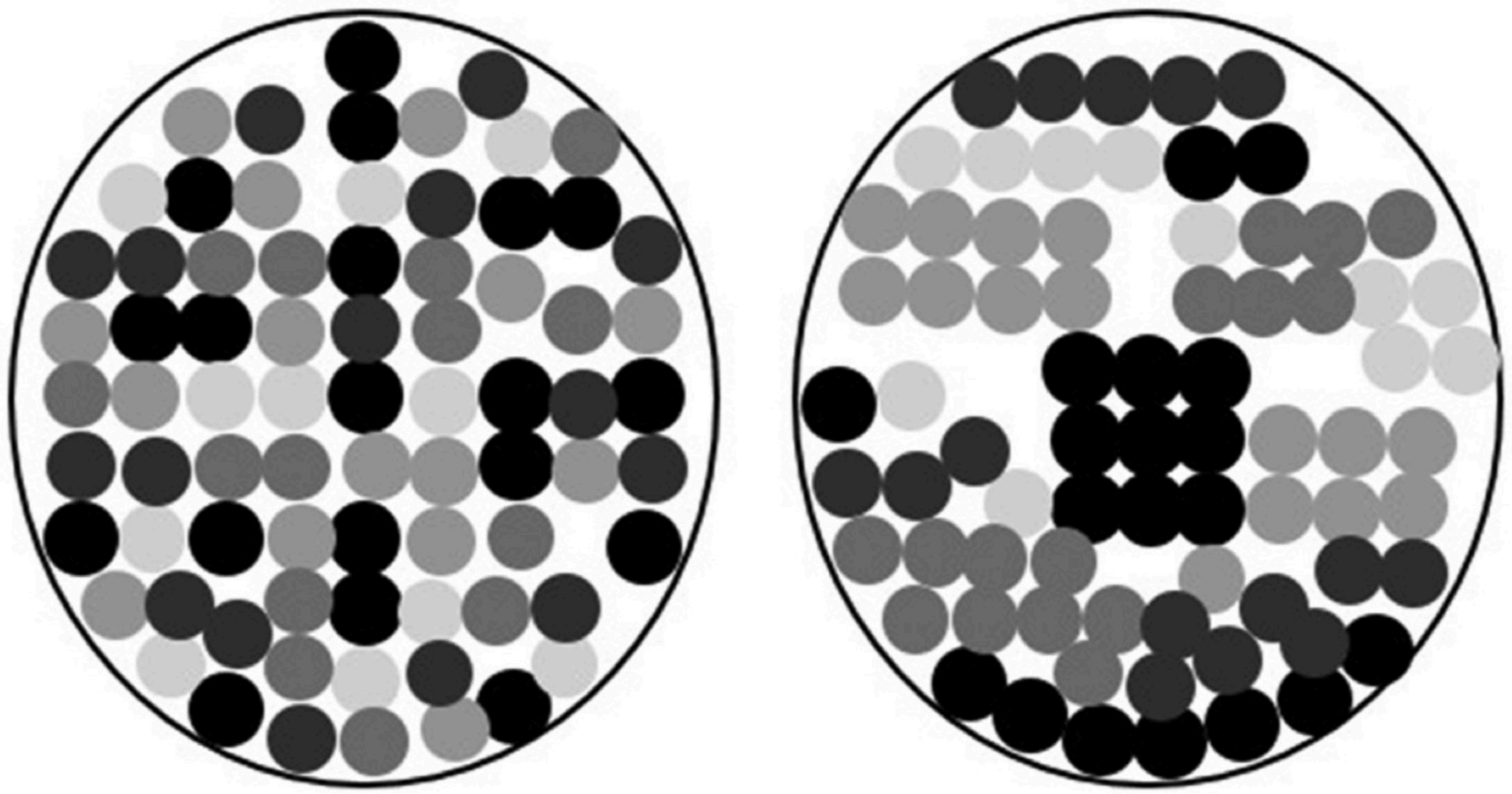


Table 1: Spectrum of Statistical-based First-Order and Higher-Order Texture Features

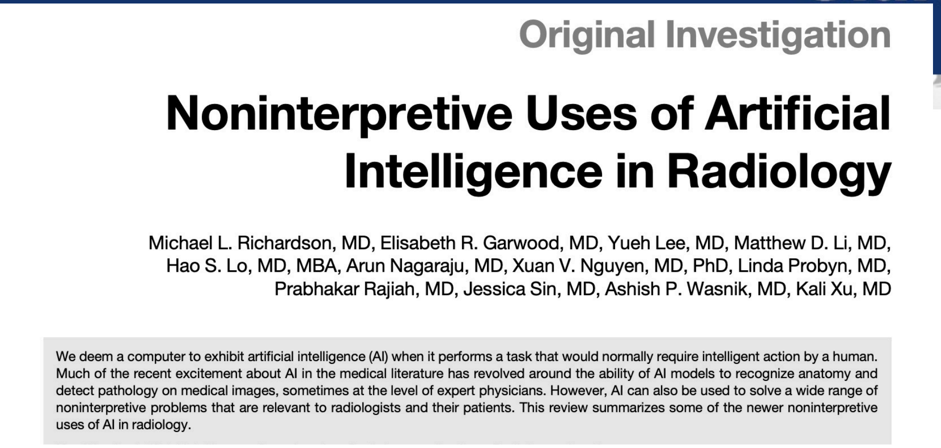
Texture Feature	Level/Order	Description	Examples	Comments
Intensity of pixel histogram	First order	Histogram where x-axis represents pixel/voxel gray level and y-axis represents frequency of occurrence (Fig 2)	Mean gray-level intensity, threshold, standard deviation or variance of the pixel histogram, skewness, kurtosis, first-order entropy, mean of the positive pixels (MPP)	Takes into account only pixel intensity, not spatial location or relationship of pixels First-order entropy is the irregularity or complexity of pixel intensities
Run-length matrix	Second order	Adjacent or consecutive pixels/voxels of a single gray level in a given direction	Run-length nonuniformity, gray-level nonuniformity, long-run emphasis, short-run emphasis, fraction	Similar to co-occurrence matrix, takes into account both pixel intensity and spatial relationships
Gray-level co-occurrence matrix	Second order	How often pairs of pixels with specific values in a specified spatial range occur in an image	Contrast, uniformity, second-order entropy, sum of variance, sum of averages, sum of entropy	...
Advanced metrics	Higher order	Comparing differences and relationships between multiple pixels/voxels	Hundreds: autoregressive model, Haar wavelet (wavelet energy), geometry parameters, neighborhood gray-tone difference matrix	...

Applicazioni in oncologia
Caratterizzazione istologica

PRIMO PASSO: SEGMENTAZIONE ED ESTRAZIONE PARAMETRI TEXTURE



Same number of grey circle different distribution different texture parameters


Original Investigation

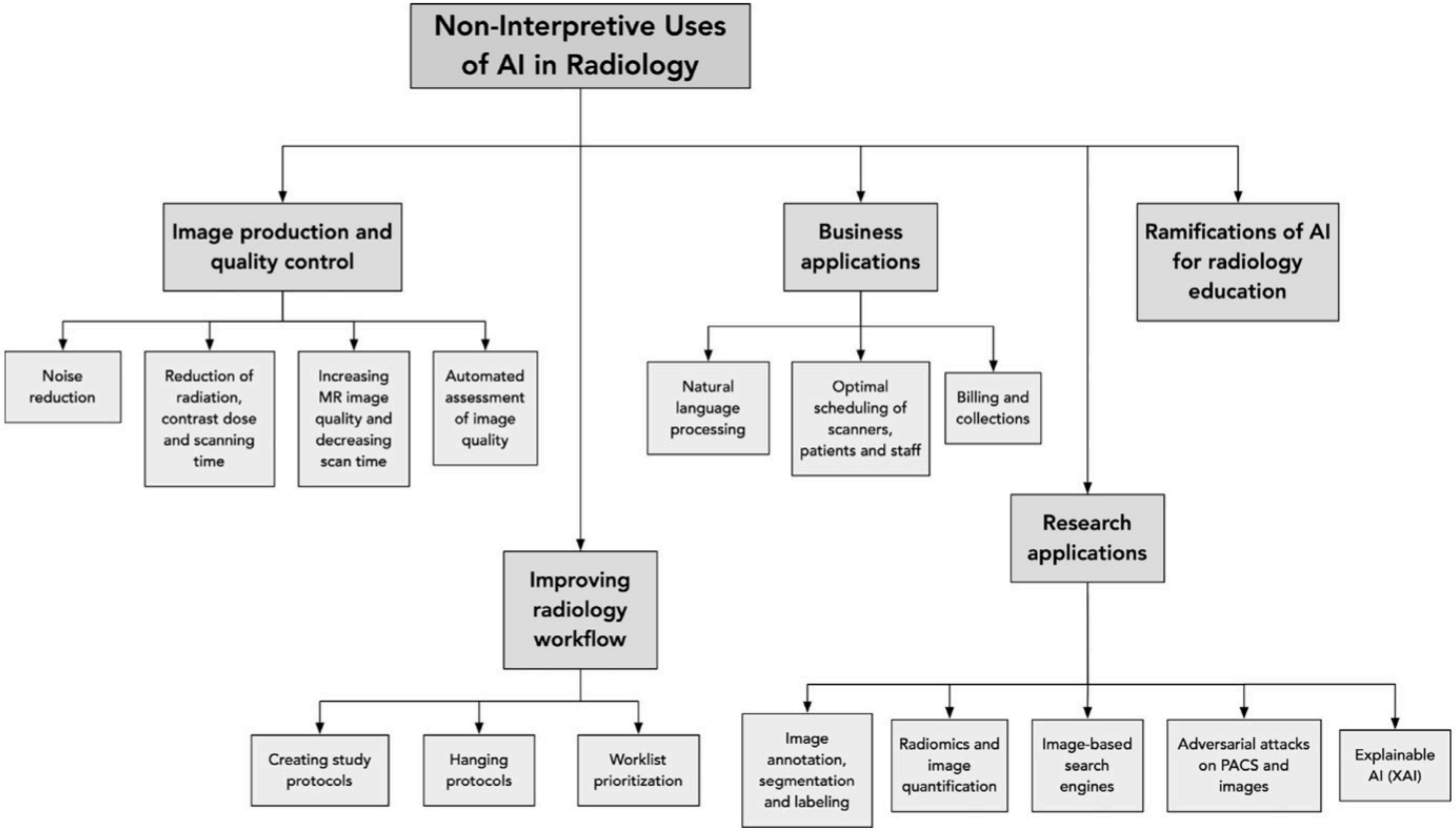
Noninterpretive Uses of Artificial Intelligence in Radiology

Michael L. Richardson, MD, Elisabeth R. Garwood, MD, Yueh Lee, MD, Matthew D. Li, MD, Hao S. Lo, MD, MBA, Arun Nagaraju, MD, Xuan V. Nguyen, MD, PhD, Linda Probyn, MD, Prabhakar Rajiah, MD, Jessica Sin, MD, Ashish P. Wasnik, MD, Kali Xu, MD

We deem a computer to exhibit artificial intelligence (AI) when it performs a task that would normally require intelligent action by a human. Much of the recent excitement about AI in the medical literature has revolved around the ability of AI models to recognize anatomy and detect pathology on medical images, sometimes at the level of expert physicians. However, AI can also be used to solve a wide range of noninterpretive problems that are relevant to radiologists and their patients. This review summarizes some of the newer noninterpretive uses of AI in radiology.

APPLICAZIONI NON INTERPRETATIVE DELL'AI

Accademic Radiology, 2020



Imaging production and quality control

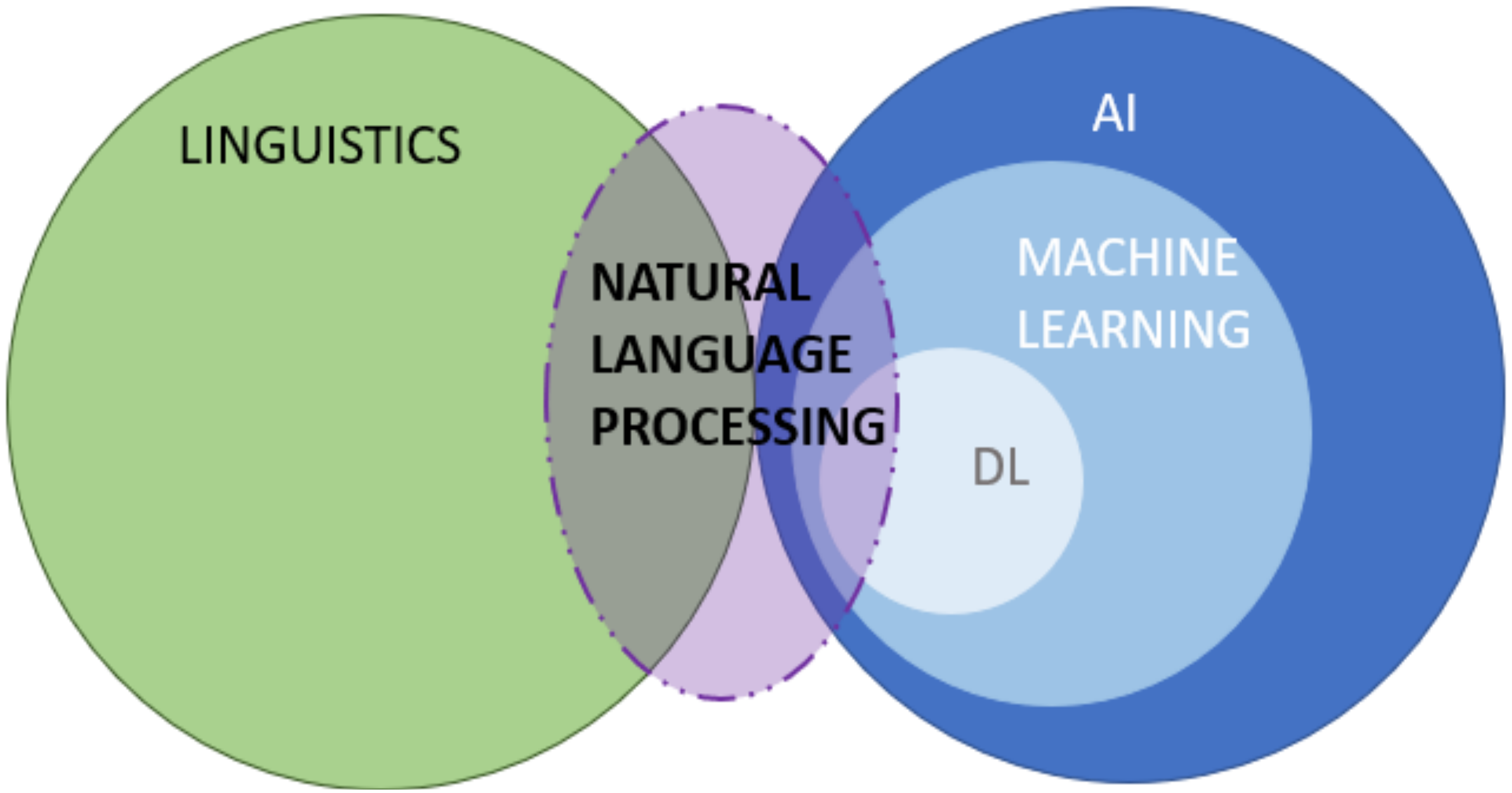
- Noise Reduction
- Reduction of Radiation, Contrast Dose, and Scanning Time
- Increasing MR Image Quality and Decreasing Scan Time
- Increasing MR Image Quality and Decreasing Scan Time
- Automated Assessment of Image Quality
- Hanging Protocols

BUSINESS APPLICATIONS

- Natural languages processing
- Hanging Protocols
- Optimal Scheduling of Scanners, Patients, and Staff
- Billing and collection

Reports are more then words, they are DATA: Natural Language Processing

Natural language processing (NLP) is any computer-based methods that convert free-text into a computer manageable structured data. Thus, NLP stands halfway between linguistics and computer-science.



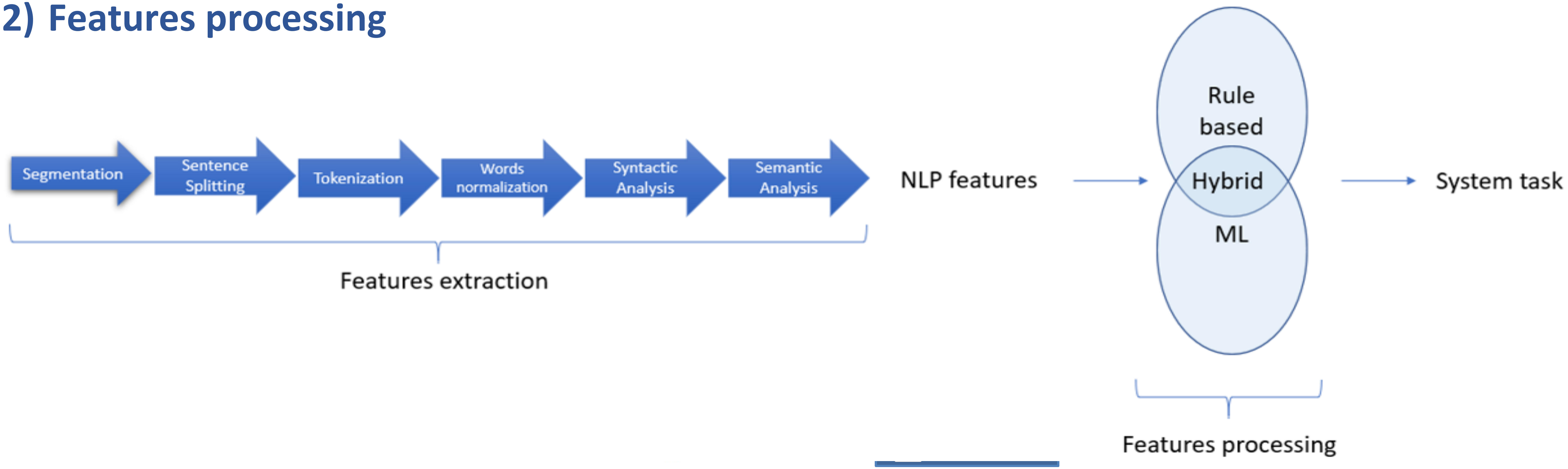
Fanni S.C., Gabelloni M., Alberich-Bayarri A., Neri E. (2022) Structured Reporting and Artificial Intelligence. In: Fatehi M., Pinto dos Santos D. (eds) Structured Reporting in Radiology.

From words to data

We can briefly summarize the entire process in two steps:

1) **Features extraction**

2) **Features processing**



Natural Language Processing applications in radiology

NLP applications in radiology are extremely numerous and continuously increasing:

- ❑ **Classification**
- ❑ **Extraction**
- ❑ **Diagnostic surveillance**
- ❑ **Enrollment of cohort for research studies**
- ❑ **Structured reporting**
- ❑ Others (Identify follow-up recommendations, Imaging protocols determinations, Quality assessment)

Natural Language Processing applications : Extraction

Extraction of BI-RADS findings from breast ultrasound reports in Chinese using deep learning approaches

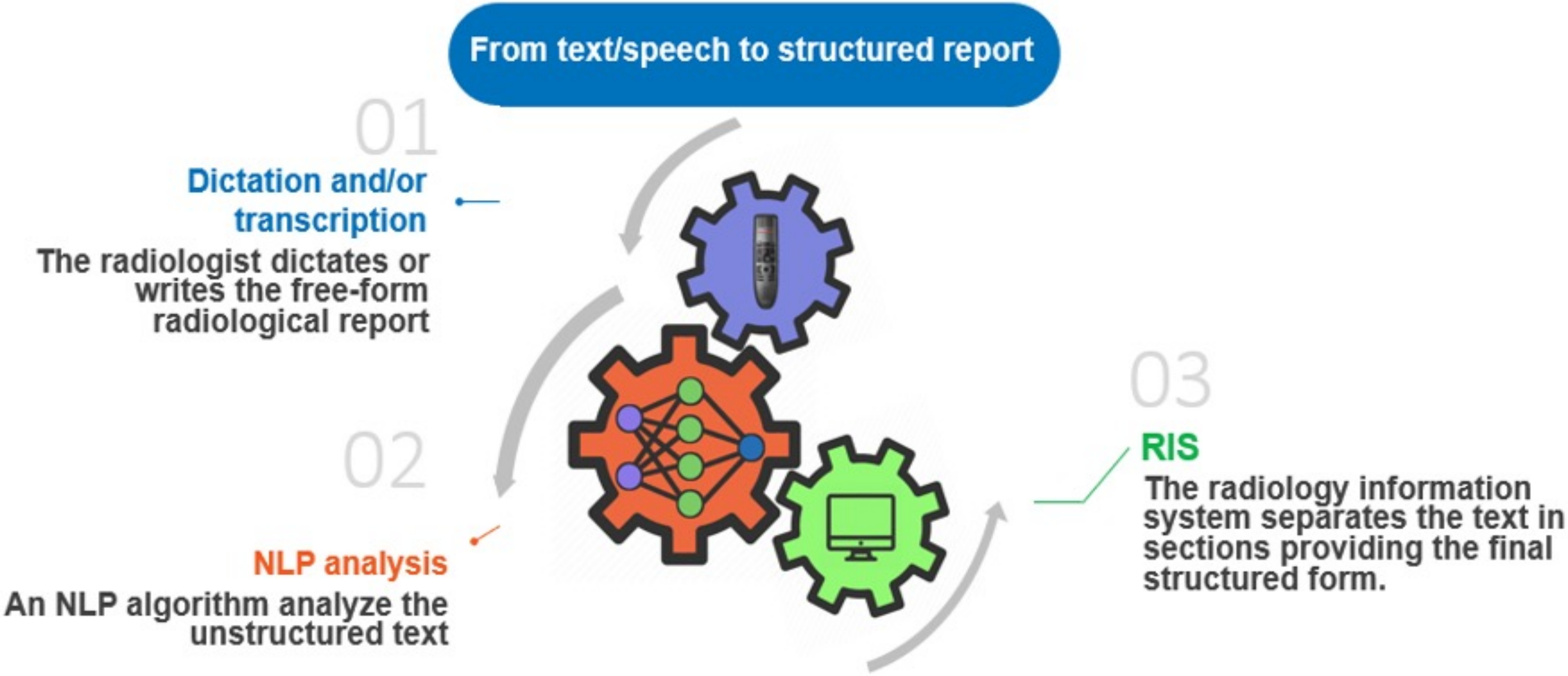
Shumei Miao[a,b,1], Tingyu Xu[a,b,1], Yonghui Wu[c,1], Hui Xie[d], Jingqi Wang[c], Shenqi Jing[a,b], Yaoyun Zhang[c], Xiaoliang Zhang[a,b], Yinshuang Yang[a,b], Xin Zhang[a,b], Tao Shan[a,b], Li Wang[e], Hua Xi

Method	Precision	Recall	F1
Rule	0.874	0.823	0.848
CRFs	0.900	0.863	0.881
RNN	0.911	0.898	0.904

Entity Type	# in test set	Precision	Recall	F1
Alder	15	1.0	0.75	0.857
Architectural-distortion	22	0	0	0
Calcifications	30	0.727	0.615	0.667
Ductchanges	52	0.589	0.667	0.625
Echo	1462	0.912	0.920	0.916
Elasticity-assessment	60	0.800	0.727	0.762
Hardness-ratio	19	0.667	0.667	0.667
Location	2301	0.913	0.895	0.904
LymphNode	399	0.901	0.812	0.854
Margin	820	0.962	0.944	0.953
Masses	158	0.927	0.950	0.938
Negation	655	0.990	0.951	0.970
Orientation	26	1.00	0.778	0.875
Posterior-features	31	0.800	0.889	0.842
Resistance-index	243	0.635	0.702	0.667
Shape	461	0.931	0.864	0.896
Size	1440	0.967	0.980	0.974
Skin	131	0.375	0.484	0.423
Tissue-composition	14	0	0	0
Vascularity	1032	0.925	0.943	0.934
Others	20	0	0	0
Overall	9391	0.911	0.898	0.904

Error type	Example	
	Gold standard	**Prediction**
Missing modifiers	Calcifications:***点***片状钙化 ***Punctate***, lamellar calcification	Calcifications:片状钙化 lamellar calcification
Rare patterns of entities	Margin: ***壁毛糙*** Wall hair rough	None
Annotation inconsistence	Location: ***较大***位于 7 点钟方向距乳头 20mm 处 ***Large***, located at 7 o'clock, away from the nipple 20mm Location: 位于 10 点钟方向，距乳头约 20mm 处 located at 10 o'clock, about 20mm from the nipple	Location: 位于 7 点钟方向距乳头 20mm 处 located at 7 o'clock, away from the nipple 20mm Location: ***较大***位于 10 点钟方向，距乳头约 20mm 处 ***Larger***, located at 10 o'clock, about 20mm from the nipple
Multiple entities recognized as one	Location:***右侧乳腺*** ***right breast*** Tissue-composition: ***回声呈不均匀型*** ***revealed low heterogeneous echo***	Location:***右侧乳腺***保乳及放疗后，双侧乳腺背景***回声呈不均匀型*** After ***right breast*** conserving and radiotherapy, the bilateral mammary gland ***revealed low heterogeneous echo***

Natural Language Processing applications : Structured reporting



Società Italiana di Radiologia Medica e Interventistica

The project: SIRM Foundation and EBIT
AI assisted structured reporting of lung CT in COVID 19 patients

Aim: unstructured reports into structured reports.

Material and Methods

- Building of the structured reporting template of chest CT in COVID-19 through MRRT
- HTML Implementation within the Radiological Information System of EBIT
- Training (ground truth) (University of Pisa)
  - Retrospective enrollment of 200 CT reports with COVID-19 pneumonia
  - Dictation of unstructured reports and coherent compilation of structured report used as ground-truth
  - Automated compilation of structured reports

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Neri *et al. Insights into Imaging* (2020) 11:92
https://doi.org/10.1186/s13244-020-00901-7

Insights into Imaging

ORIGINAL ARTICLE Open Access

Structured reporting of chest CT in COVID-19 pneumonia: a consensus proposal

E. Neri[1*], F. Coppola[2], A. R. Larici[3], N. Sverzellati[4], M. A. Mazzei[5], P. Sacco[6], G. Dalpiaz[7], B. Feragalli[8], V. Miele[9] and R. Grassi[10]

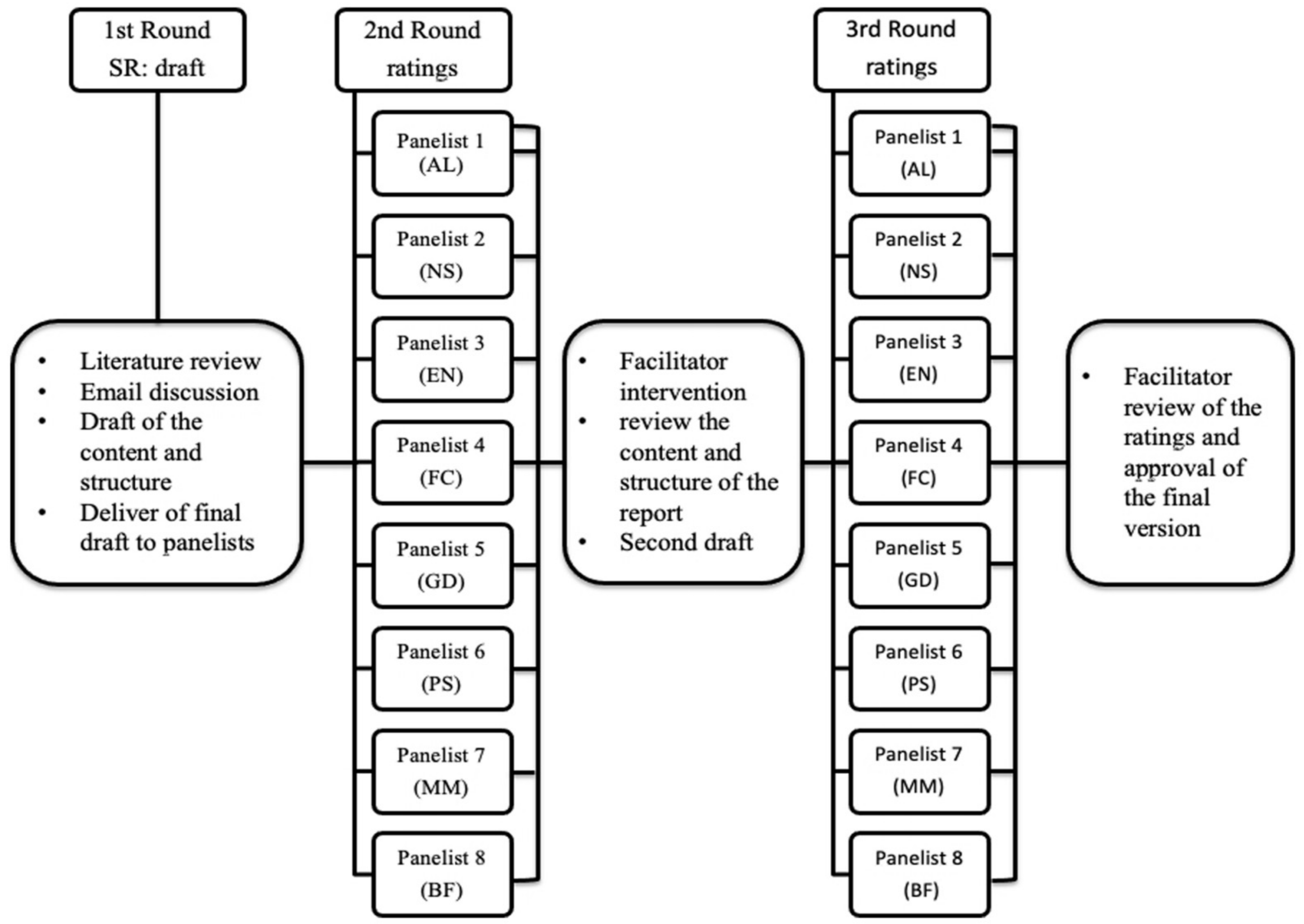
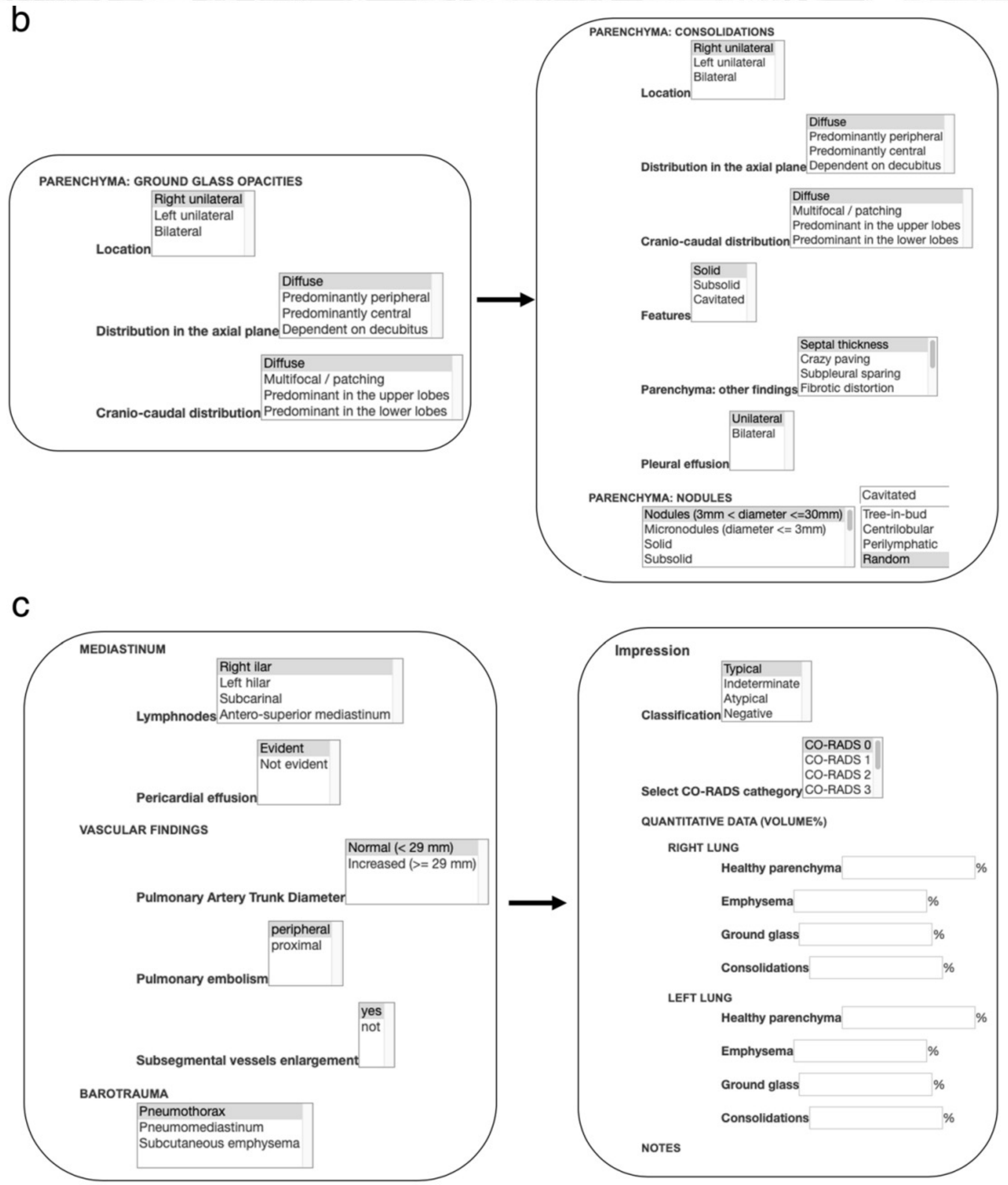


Fig. 1 Flow chart of the Delphi consensus

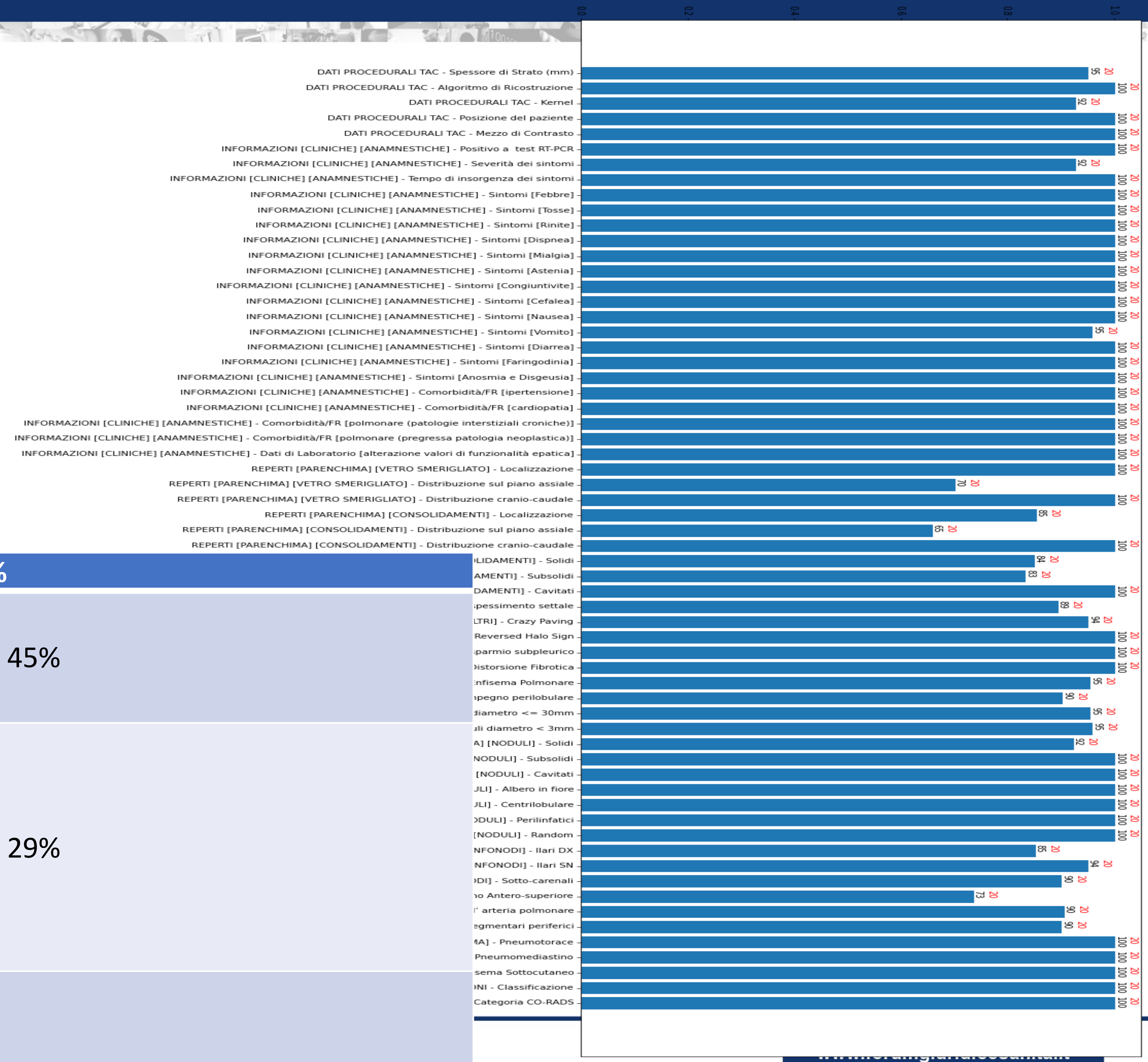


Step 1 (Consensus and Statements)

Step 2 (Structured report: MRRT compliant)

Results

- **95,8%** Mean accuracy
- **95,8 %** F1 score



Problem	Description	%
Ambiguous	ambiguous text in the report	~ 45%
Inconsistent report	the dictated data and the manually entered data did not match	~ 29%
Wrong inference	incorrect processing of the inference engine	~ 26%

A systematic review of natural language processing applied to radiology reports

Arlene Casey[1*], Emma Davidson[2], Michael Poon[2], Hang Dong[3,4], Daniel Duma[1], Andreas Grivas[5], Claire Grover[5], Víctor Suárez-Paniagua[3,4], Richard Tobin[5], William Whiteley[2,6], Honghan Wu[4,7] and Beatrice Alex[1,8]

Conclusions: Automated understanding of clinical narratives of the radiology reports has the potential to enhance the healthcare process and we show that research in this field continues to grow. Reproducibility and explainability of models are important if the domain is to move applications into clinical use. More could be done to share code enabling validation of methods on different institutional data and to reduce heterogeneity in reporting of study properties allowing inter-study comparisons. Our results have significance for researchers in the field providing a systematic synthesis of existing work to build on, identify gaps, opportunities for collaboration and avoid duplication.

triple those in 2015. Each publication is categorised into one of 6 clinical application categories. Deep learning use increases in the period but conventional machine learning approaches are still prevalent. Deep learning remains challenged when data is scarce and there is little evidence of adoption into clinical practice. Despite 17% of studies reporting greater than 0.85 F1 scores, it is hard to comparatively evaluate these approaches given that most of them use different datasets. Only 14 studies made their data and 15 their code available with 10 externally validating results.

Conclusions: Automated understanding of clinical narratives of the radiology reports has the potential to enhance the healthcare process and we show that research in this field continues to grow. Reproducibility and explainability of models are important if the domain is to move applications into clinical use. More could be done to share code enabling validation of methods on different institutional data and to reduce heterogeneity in reporting of study properties allowing inter-study comparisons. Our results have significance for researchers in the field providing a systematic

Casey *et al. BMC Med Inform Decis Mak* (2021) 21:179
https://doi.org/10.1186/s12911-021-01533-7

BMC Medical Informatics and Decision Making

Knowledge and Information Systems (2023) 65:463–516
https://doi.org/10.1007/s10115-022-01779-1

REVIEW

Check for updates

Information extraction from electronic medical documents: state of the art and future research directions

Mohamed Yassine Landolsi[1] · Lobna Hlaoua[1] · Lotfi Ben Romdhane[1]

Abstract

In the medical field, a doctor must have a comprehensive knowledge by reading and writing narrative documents, and he is responsible for every decision he takes for patients. Unfortunately, it is very tiring to read all necessary information about drugs, diseases and patients due to the large amount of documents that are increasing every day. Consequently, so many medical errors can happen and even kill people. Likewise, there is such an important field that can handle this problem, which is the information extraction. There are several important tasks in this field to extract the important and desired information from unstructured text written in natural language. The main principal tasks are named entity recognition and relation extraction since they can structure the text by extracting the relevant information. However, in order to treat the narrative text we should use natural language processing techniques to extract useful information and features. In our paper, we introduce and discuss the several techniques and solutions used in these tasks. Furthermore, we outline the challenges in information extraction from medical documents. In our knowledge, this is the most comprehensive survey in the literature with an experimental analysis and a suggestion for some uncovered directions.

cancers

MDPI

Systematic Review

The Use of Artificial Intelligence (AI) in the Radiology Field: What Is the State of Doctor–Patient Communication in Cancer Diagnosis?

Alexandra Derevianko [1], Silvia Francesca Maria Pizzoli [2,*], Filippo Pesapane [3], Anna Rotili [3], Dario Monzani [4], Roberto Grasso [1,2], Enrico Cassano [3] and Gabriella Pravettoni [1,2]

YALE JOURNAL OF BIOLOGY AND MEDICINE 96 (2023), pp.407-414.

YALE JOURNAL OF BIOLOGY AND MEDICINE
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MINI-REVIEW

Artificial Intelligence to Improve Patient Understanding of Radiology Reports

Kanhai Amin[a,*], Pavan Khosla[b], Rushabh Doshi[b], Sophie Chheang[c], and Howard P. Forman[c,d,e]

[a]Yale University, New Haven, CT, USA; [b]Yale School of Medicine, New Haven, CT, USA; [c]Department of Radiology and Biomedical Imaging, Yale School of Medicine, New Haven, CT, USA; [d]Yale School of Management, New Haven, CT, USA; [e]Department of Health Policy and Management, Yale School of Public Health, New Haven, CT, USA

Simple Summary: Artificial Intelligence (AI) has been increasingly used in radiology to improve diagnostic procedures over the past decades. The application of AI at the time of cancer diagnosis also creates challenges in the way doctors should communicate the use of AI to patients. The present systematic review deals with the patient's psycho-cognitive perspective on AI and the interpersonal skills between patients and physicians when AI is implemented in cancer diagnosis communication. Evidence from the retrieved studies pointed out that the use of AI in radiology is negatively associated with patient trust in AI and patient-centered communication in cancer disease.

Direct communication between radiologists and patients improves the quality of imaging reports

Malpractice | Published: 28 April 2021

Volume 31, pages 8725–8732, (2021) Cite this article

Radiology

ORIGINAL RESEARCH • HEALTH POLICY AND PRACT

Assessment of Claimant, Clinical, and Financial Characteristics of Teleradiology Medical Malpractice Cases

Adam C. Schaffer, MD, MPH • Tarek Zawi, BA • Jonathan S. Einbinder, MD, MPH • Luke Sato, MD • Aaron D. Sodickson, MD, PhD

From the CRICO/Risk Management Foundation of the Harvard Medical Institutions, Boston, Mass (A.C.S., T.Z., J.S.E., L.S.); and Department of Medicine (A.C.S., J.S.E., L.S.) and Department of Radiology, Division of Emergency Radiology (A.D.S.), Brigham and Women's Hospital, Harvard Medical School, 75 Francis St, PBB-B-422, Boston, MA 02215. Received October 16, 2023; revision requested November 21; revision received January 25, 2024; accepted February 13. **Address correspondence to** A.C.S. (email: *aschaffer@bwh.harvard.edu*).

Conflicts of interest are listed at the end of this article.

See also the editorial by Mezrich in this issue.

Radiology 2024; 311(1):e232806 • https://doi.org/10.1148/radiol.232806 • Content codes: SQ HP

Conclusion: Compared with radiology cases, teleradiology cases had higher clinical and financial severity and were more likely to involve issues with communication.

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ORIGINAL ARTICLE | VOLUME 20, ISSUE 10, P998-1003, OCTOBER 2023

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ChatGPT-4 Assistance in Optimizing Emergency Department Radiology Referrals and Imaging Selection

Yiftach Barash, MD, MSc • Eyal Klang, MD • Eli Konen, MD • Vera Sorin, MD

Published: July 07, 2023 • DOI: https://doi.org/10.1016/j.jacr.2023.06.009 • Check for updates

Radiology

ORIGINAL RESEARCH

BI-RADS Category Assignments by GPT-3.5, GPT-4, and Google Bard: A Multilanguage Study

Andrea Cozzi, MD, PhD • Katja Pinker, MD, PhD* • Andri Hidber, BMed • Tianyu Zhang, PhD • Luca Bonomo, MD • Roberto Lo Gullo, MD • Blake Christianson, MD • Marco Curti, MD • Stefania Rizzo, MD, PhD • Filippo Del Grande, MD, MBA, MHEM • Ritse M. Mann, MD, PhD** • Simone Schiaffino, MD***

From the Imaging Institute of Southern Switzerland (IIMSI), Ente Ospedaliero Cantonale, Via Tesserete 46, 6900 Lugano, Switzerland (A.C., L.B., M.C., S.R., F.I Imaging Service, Department of Radiology, Memorial Sloan Kettering Cancer Center, New York, NY (K.P., R.L.G., B.C.); Faculty of Biomedical Sciences, Univer Italiana, Lugano, Switzerland (A.H., S.R., F.D.G., S.S.); Department of Radiology, Netherlands Cancer Institute, Amsterdam, the Netherlands (T.Z., R.M.I of Diagnostic Imaging, Radboud University Medical Center, Nijmegen, the Netherlands (T.Z., R.M.M.); and GROW Research Institute for Oncology ar Maastricht University, Maastricht, the Netherlands (T.Z.). Received August 14, 2023; revision requested August 23; final revision received March 8, 2024; acc
Address correspondence to A.C. (email: *andrea.cozzi@gmail.com*).

K.P. is supported in part by a National Cancer Institute Cancer Center Support Grant (P30 CA008748).

* A.C. and K.P. contributed equally to this work.

** R.M.M. and S.S. are co-senior authors.

Conflicts of interest are listed at the end of this article.

Radiology 2024; 311(1):e232133 • https://doi.org/10.1148/radiol.232133 • Content codes: BR AI

Background: The performance of publicly available large language models (LLMs) remains unclear for complex clinical tasks.

CONCLUSIONI

IL PAZIENTE DEVE ESSERE AL CENTRO DELL'EVOLUZIONE TECNOLOGICA

Stephen Hawking, collegato al web summit di Lisbona del 2017, ha sollevato la questione dicendo che "*Le nostre Intelligenze Artificiali devono fare quel che vogliamo che facciano*", sostenendo che non possiamo ancora prevedere che cosa davvero sarà possibile quando la mente umana sarà amplificata dall'Intelligenza Artificiale, ma che non possiamo ignorare che vi siano anche dei pericoli e il modo migliore di fronteggiarli è quello di identificarli e non ignorare il fatto che le nostre vite verranno trasformate.

Seguendo il ragionamento di Hawking, il vero "potere" sarà la conoscenza approfondita di questo fenomeno. È importante ricordare che *«Ci si preoccupa delle macchine che si umanizzano, ma il vero problema oggi sono i medici che sono diventati delle macchine»*

Ore 16.00 – 18.00	**NUOVE TECNOLOGIE ED AI: TRA OPPORTUNITÀ E RISCHI** **LE NUOVE FRONTIERE DELLA RESPONSABILITÀ**
Presiedono	
Vasco Giannotti	*Presidente Forum Risk Management in Sanità*
Fabio Canini	*Ministero della Salute*
Intervengono	
Federico Gelli	*Direttore Direzione Generale Sanità, Welfare e Coesione sociale Regione Toscana*
Maurizio Hazan	*Studio Legale Taurini Hazan, Presidente Fondazione Italia in Salute*
Pasquale Giuseppe Macrì	*Responsabile Centro Gestione Rischio Clinico Regione Toscana,* *Membro Tavolo Tecnico Ministero della Salute*
Marco Rossetti	*Consigliere 3° Sezione Civile Cassazione*
Andrea Simoni	*Segretario Generale Fondazione Bruno Kessler*
Daniela Bardoni	*Patrocinante in Cassazione- Associazione Sanitas et Cura*
Riccardo Ferrari	*Esperto in AI applicato alla radiodiagnostica AO San Camillo Forlanini RM*
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Radiodiagnostica Emergenza Urgenza
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Presidente *della sezione di Informatica ed intelligenza artificiale in Radiologia della SIRM 2025-2026*
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