فرصت ها و چالشهای هوش مصنوعی در سلامت دستگاه گوارش

31 Khordad 1403 IAGH Webinar

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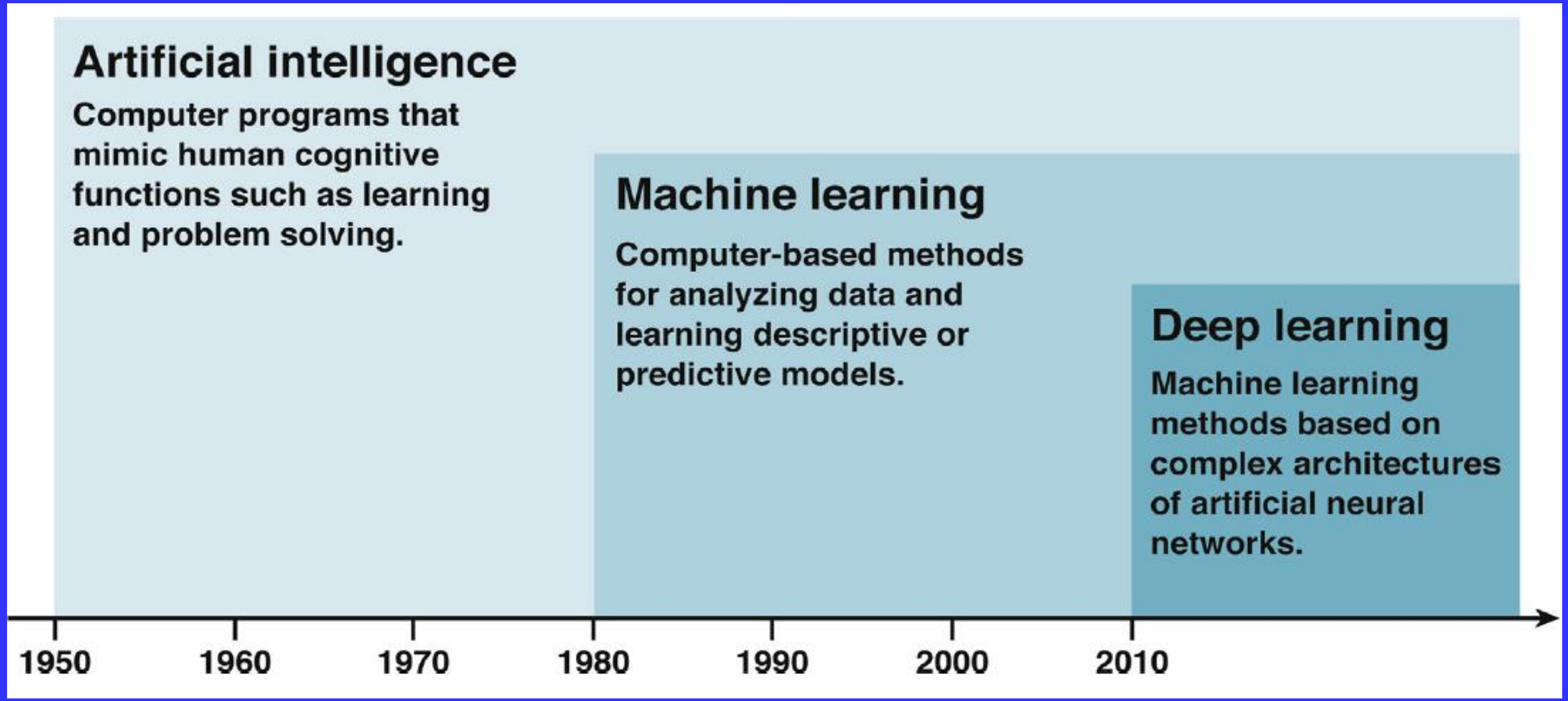
Artificial Intelligence (AI)

- The term artificial intelligence (AI) was first introduced in the 1950s and refers to the application of computers to perform complex tasks, such as solving problems and making nuanced decisions, that have traditionally been associated with human intelligence.
- Interest in AI-driven health care and medicine has been exploding in recent decades, owing largely to the vast increase in data available since the establishment of the electronic health record (EHR).

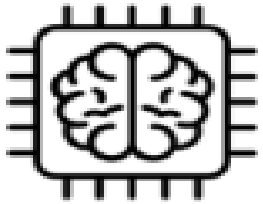
Artificial Intelligence Terminology

Artificial intelligence	Machine intelligence that has cognitive functions similar to those of humans such as "learning" and "problem solving."
Machine learning	Mathematical algorithms which is automatically built from given data (known as input training data) and predicts or makes decisions in uncertain conditions without being explicitly programmed
Support vector machines	Discriminative classifier formally defined by an optimizing hyperplane with the largest functional margin
Artificial neural networks	Multilayered interconnected network which consists of an input, hidden connection (between the input and output layer), and output layer
Deep learning	Subset of machine learning technique that composed of multiple-layered neural network algorithms
Convolutional neural networks	Specific class of artificial neural networks that consists of (1) convolutional and pooling layers, which are the two main components to extract distinct features; and (2) fully connected layers to make an overall classification
Overfitting	Modelling error which occurs when a certain learning model tailors itself too much on the training dataset and predictions are not well generalized to new datasets
Spectrum bias	Systematic error occurs when the dataset used for model development does not adequately represent or reflect the range of patients who will be applied in clinical practice (target population)

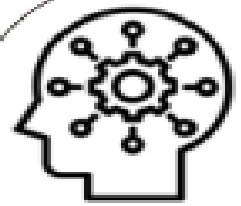
Timeline of AI main concepts.



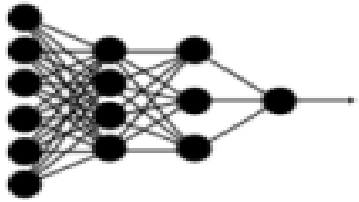
Artificial Intelligence Terminology



Artificial intelligence: Any technique making a computer or software mimic human function such as learning and problem solving



Machine learning: Technique of artificial intelligence for the automatic learning and improving without being explicitly programmed



Deep learning: Technique of machine learning with multi-layered neural networks algorithms

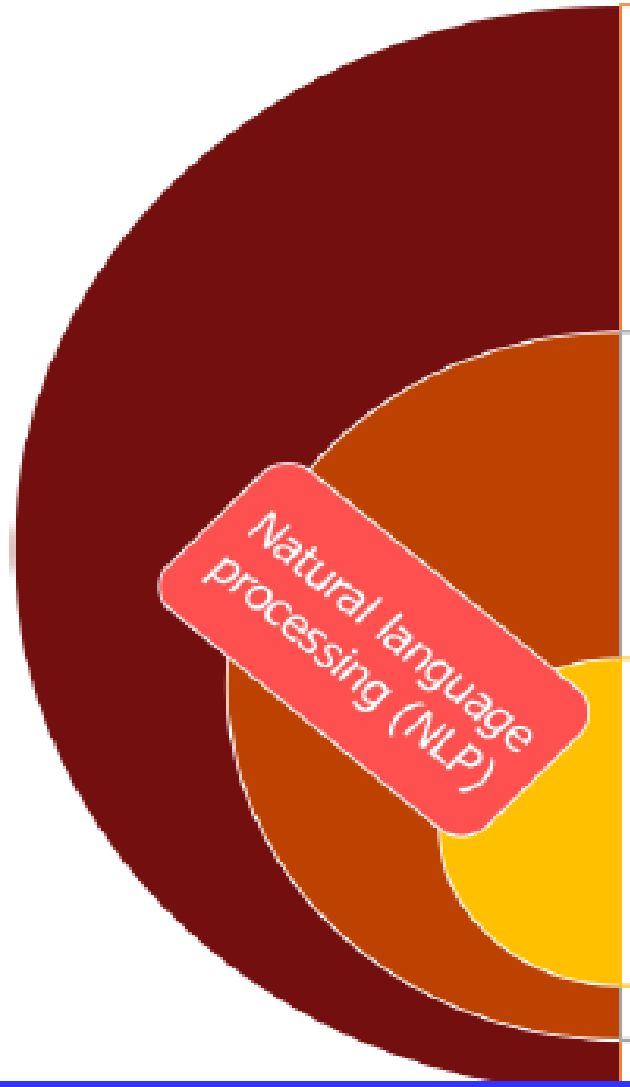
The current emphasis of AI in medicine is a direct response to the challenges facing health-care systems

- In fact, from 2008 to 2018, over **23,000 papers concerning the application of AI in health care have been published.**
- The number of published paper has reached to more than **250 000,in 2024**.
- The current emphasis of AI in medicine is a direct response to the challenges facing health-care systems including increasingly complex patients, higher billing and coding requirements, and a growing population that leaves less time for interactions between a health-care provider and their patients than ever before.
- The hope is for a future where **AI-driven health care can lead to improvements through** all aspects of patient care by leveraging the vast quantities of data currently stored in the EHR

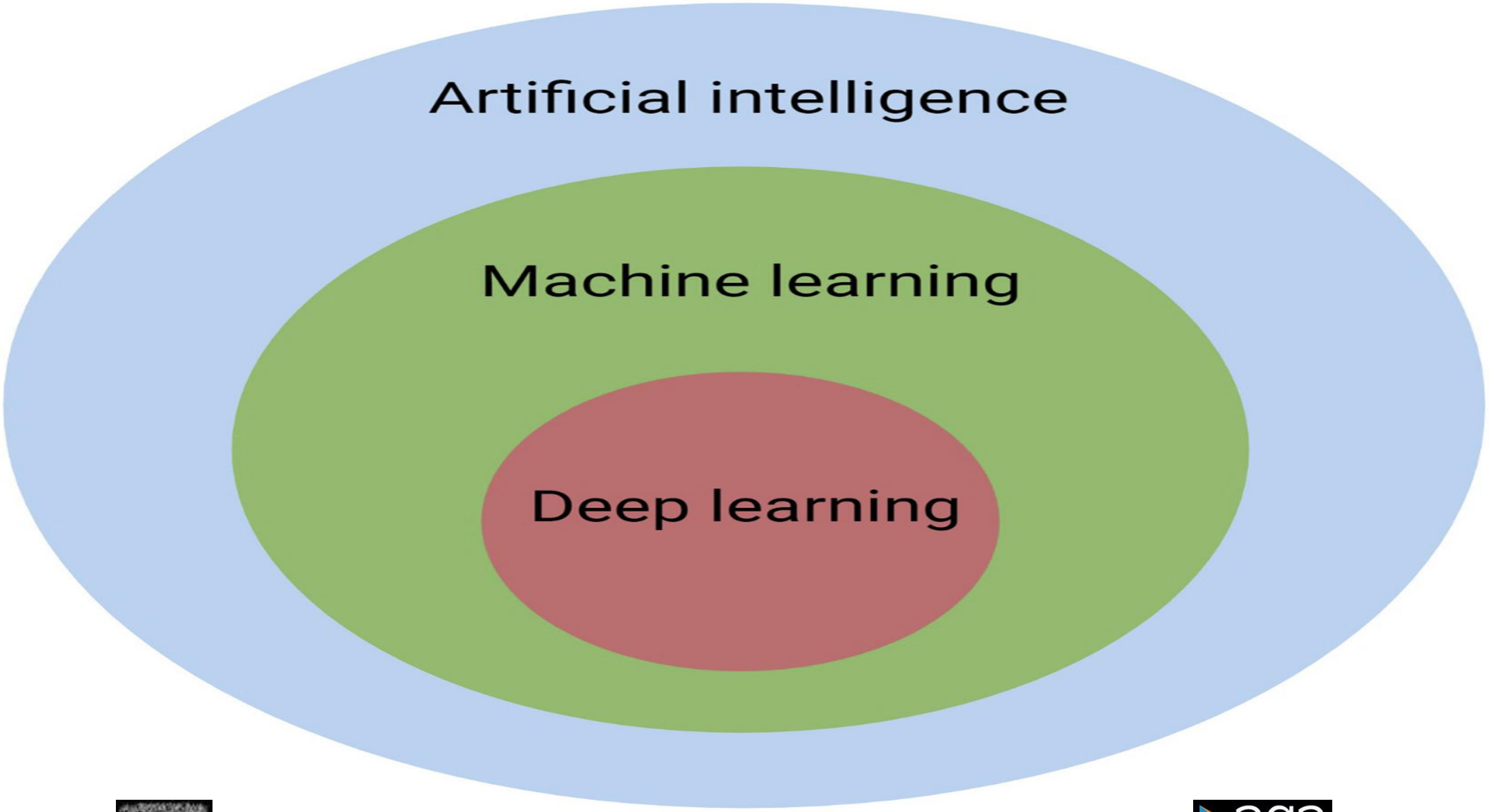
While AI as a concept has existed since the 1950s, all AI is not the same 3 types of AI

- **AI 1.0** includes symbolic AI, which attempts to encode human knowledge into computational rules, as well as probabilistic models.
- **AI 2.0** began with **deep learning and machine learning**,, in which models learn from examples labeled with ground truth. AI.2 Brought many advances but had risk of **Catastrophic forgetting**
- **AI 3.0** Foundation Models and **Generative AI** have fundamentally new capabilities, as well as new kinds of risks, such as **hallucinations.**

Primary concepts of artificial intelligence.



Artificial intelligence	Umbrella term summarizing computer models based on human intelligence
Machine learning	Subset of artificial intelligence for recognition of patterns in complex data
Deep learning	Subset of machine learning with automatic classification into output groups



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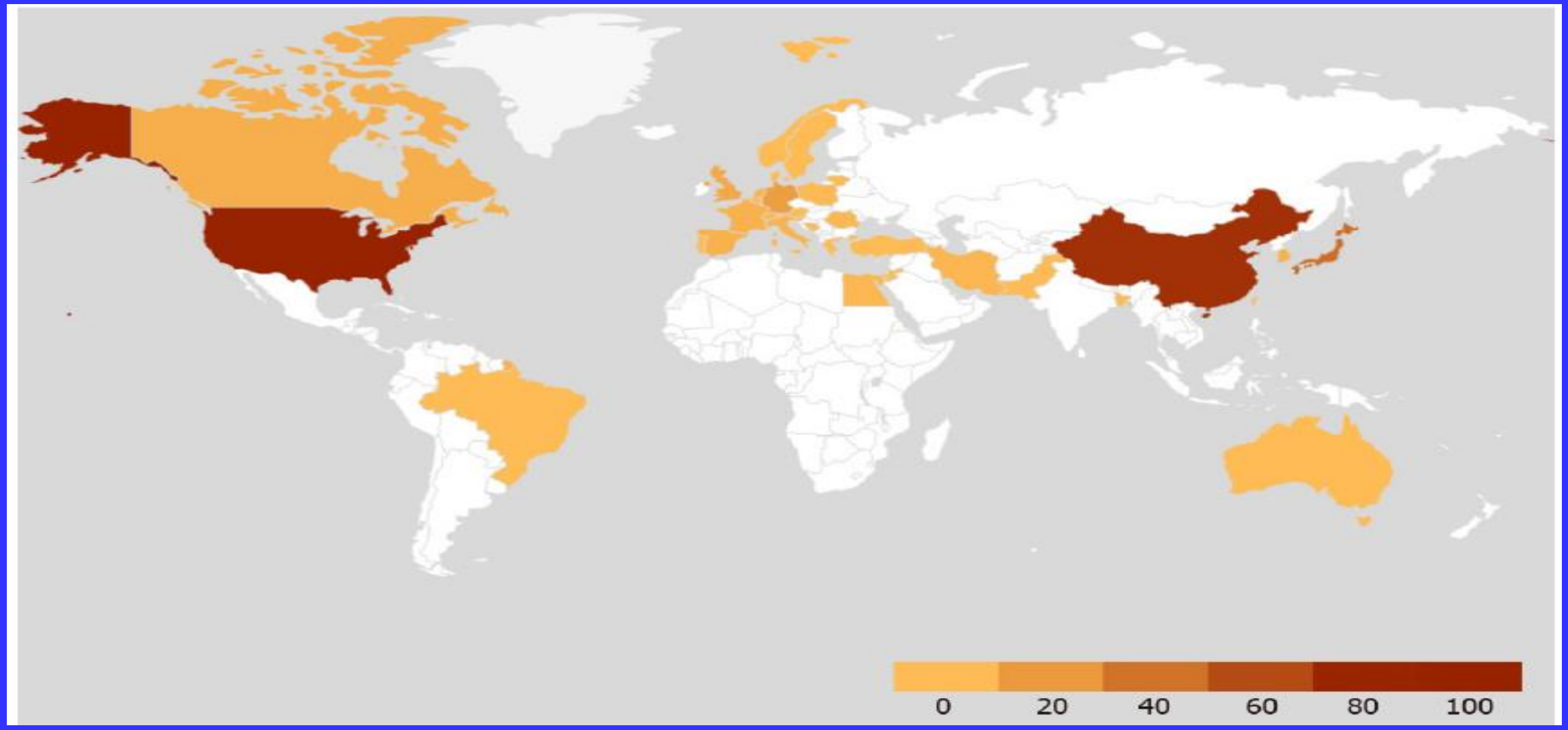
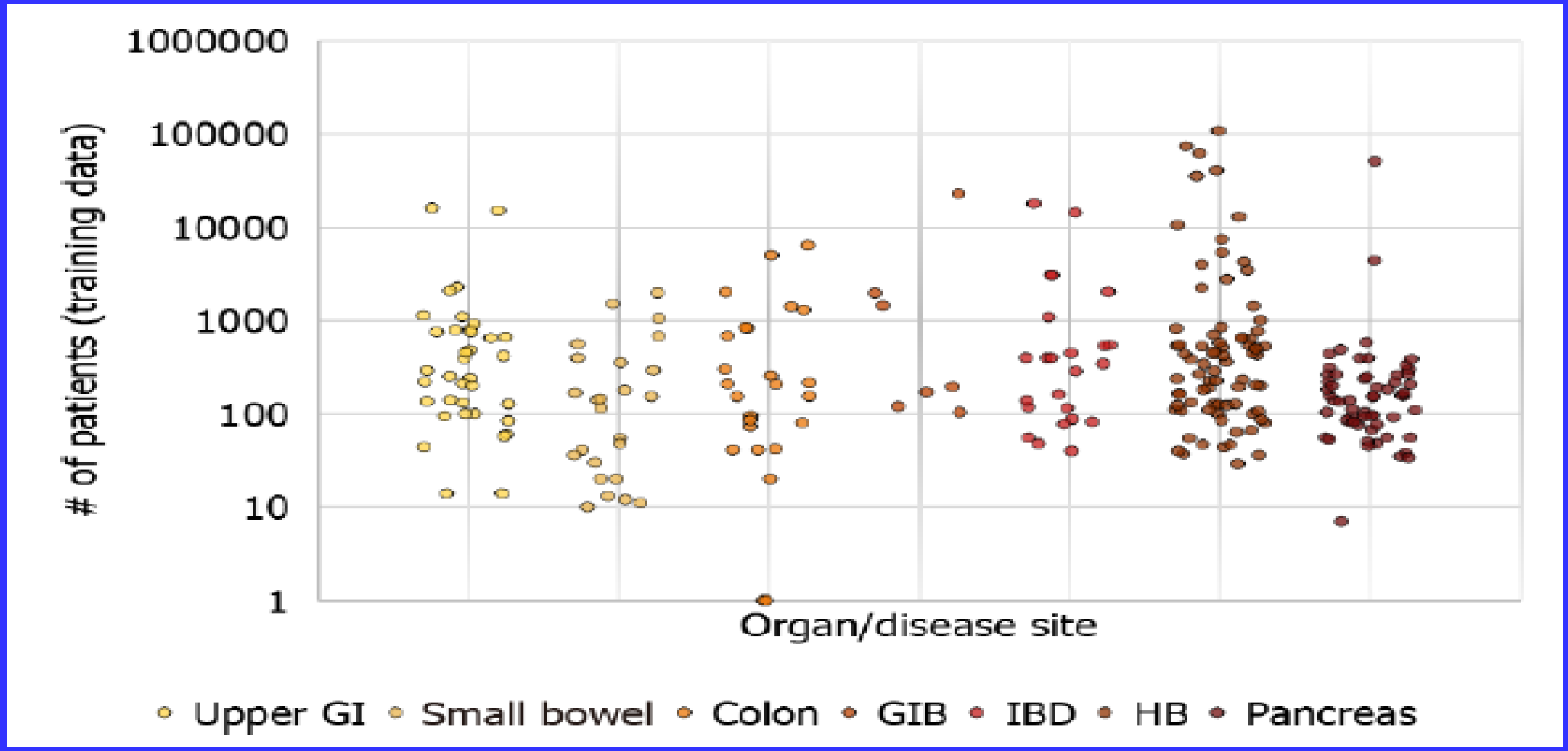
Artificial Intelligence (AI) 1.0, 2.0, and 3.0

	AI 1.0 Symbolic AI and probabilistic models	AI 2.0 Deep learning	AI 3.0 Foundation models
Approximate beginning year	*1950s*	*2011*	*2018-2022*
Core functionality and key features	Follows directly encoded rules (if-then rules or decision trees)	Predicts and/or classifies information Task-specific (1 task at a time); requires new data and retraining to perform new tasks	Generates new content (text, sound, images) Performs different types of tasks without new data or retraining; prompt creates new model behaviors
Training method	Rules based on expert knowledge are hand-encoded in traditional programming	Learning patterns based on examples labeled as ground truth	Self-supervised learning from large datasets to predict the next word or sentence in a sequence
Performance capabilities	Follows decision path encoded in its rules. *Eg, ask a series of questions to determine whether a picture is a cat or a dog.*	Classifies information based on training: *"Is this a cat or a dog?"* *"How many dogs will be in the park at noon?"*	Interprets and responds to complex questions: *"Explain the difference between a cat and a dog."*
Examples of performance	IBM's Deep Blue beat the world champion in chess **Health care:** Rule-based clinical decision support tools	Photo searching without manual tagging, voice recognition, language translation **Health care:** diabetic retinopathy detection, breast cancer and lung cancer screening, skin condition classification, predictions based on electronic health records	Writing assistants in word processors, software coding assistants, chatbots **Health care:** Med-PaLM and Med-PaLM-2, medically tuned large language models, PubMedGPT, BioGPT
Examples of challenges and risks	Human logic errors and bias in encoded rules lead to limited capability with real-world situations	Out-of-distribution problems (real-time data differs from training data) Catastrophic forgetting (not remembering early parts of a long sequence of text) Bias related to underlying training data	Hallucinations (plausible but incorrect responses based solely on predictions) Grounding and attribution Bias related to underlying training data and semantics of language in datasets

Geographic distribution of country from which the AI studies originated



Scatterplot depicting distribution of studies across the organ systems in gastroenterology and hepatology



Generative AI .3

- **Foundation models and generative AI .3** represent a major revolution in AI's capabilities, offering tremendous potential to improve Health care.

Applications of AI for health include:

- Diagnosis.
- Clinical care.
- Research
- Drug development.
- Health-care administration.
- Public health and surveillance.

AI large language model is a Medical Device

- All of laws, norms, and procedures fall into place.
- We may need to shift the world of generative AI from thinking less about the specific device to more about the outcomes that we want.
- AI outcomes that we want is for it to be safe, to be proven effective, and to have some transparency, particularly in clinical practice.

LLMs have been adopted faster than any consumer application in history

- **They are compelling because they facilitate human–computer interaction to mimic human communication and to generate responses to queries or data inputs that may appear human-like and authoritative.**

- **With rapid consumer adoption and uptake and in view of its potential to disrupt core social services and economic sectors, many large technology companies, start-ups and governments are investing in and competing to guide the development of generative AI.**

Generative AI .3

- **The models also have dramatically improved capabilities: interpreting truly complex questions; accepting and producing text, images, and sound; creating responses that are near-indistinguishable from those written by people; and carrying on extended conversations.**

- **Health care leaders across the ecosystem are faced with questions about where, when, and how to deploy AI and how to understand its risks, problems, and possibilities.**

Health specific large Language models

- **Med-PaLM**
- **Med-PaLM 2.**

❑**Are medically tuned foundation models, developed at Google, that reached expert-level performance on medical licensing examination–style questions.**

❑**They were also able to write long-form answers to people's health questions.**

❑**When physicians compared Med-PaLM 2's answers vs those written by physicians without knowledge of the origin, they strongly preferred the model's answers on 8 of 9 dimensions evaluated.**

Hallucinations Represent major risk in AI 3.0

- LLM models can be good at writing computer programs, but bad at Mathematics
- Why? It is because they are not doing math, they are predicting the next word in a sequence.
- They may return plausible-sounding but incorrect journal citations.
- Why? For the same reason: they are not looking things up in PubMed, they are predicting plausible next words. These “

Warning about AI Hallucinations.

- That these language models, any AI, if you ask it to extrapolate beyond what it knows it's going to start to make up things and we might call those hallucinations.

- It would be useful for these large language models like Open AI to tell us when they were hallucinating .
- They don't often do that, so you've got to be careful

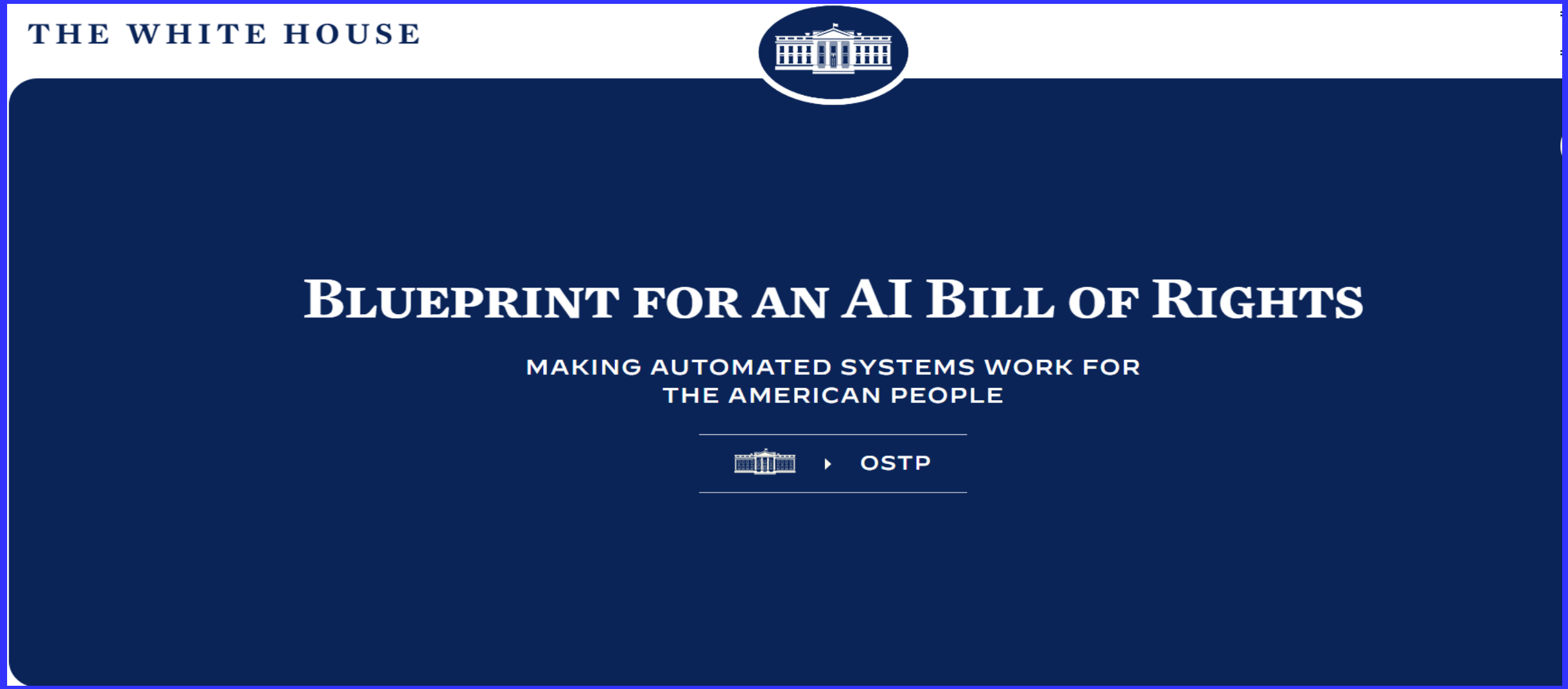
Big Data most essential enabling resources of AI.

- **Human Genome Project create a very big data opportunity.**
- **How to analyze these big data to offer a better health outcomes.**
- **Big data are the most essential enabling resources of AI.**

AI A great Challenger to Democracy

- Among the great challenges posed to democracy today is the use of technology, data, and automated systems in ways that threaten the rights of the public.
- Too often, these tools are used to limit our opportunities and prevent our access to critical resources or services.
- Unchecked social media data collection has been used to threaten people's opportunities, undermine their privacy, or pervasively track their activity—often without their knowledge or consent.

Protect the public from harm in a proactive and ongoing manner



BRIEFING

EU Legislation in Progress

European Parliament

Artificial intelligence liability directive

OVERVIEW

The European Commission published a proposal for a directive on adapting non-contractual civil liability rules to artificial intelligence (the 'AI liability directive') in September 2022. The Commission proposes to complement and modernise the EU liability framework to introduce new rules specific to damages caused by AI systems. The new rules intend to ensure that persons harmed by AI systems enjoy the same level of protection as persons harmed by other technologies in the EU. The AI liability directive would create a rebuttable 'presumption of causality', to ease the burden of proof for victims to establish damage caused by an AI system. It would furthermore give national courts the power to order disclosure of evidence about high-risk AI systems suspected of having caused damage. Stakeholders and academics are questioning, inter alia, the adequacy and effectiveness of the proposed liability regime, its coherence with the artificial intelligence act currently under negotiation, its potential detrimental impact on innovation, and the interplay between EU and national rules.



World Health Organization

Ethics and governance of artificial intelligence for health

Guidance on large multi-modal models

Potential benefits and risks in various uses of LMMs in health care

Use	Potential or proposed benefits	Potential risks
Diagnosis and clinical care	Assist in managing complex cases and review of routine diagnoses Reduce the communication workload of health-care providers ("keyboard liberation") Provide novel insights and reports from various unstructured forms of health data	Inaccurate, incomplete or false responses Poor quality training data Bias (of training data and responses) Automation bias Degradation of skills (of health-care professionals) Informed consent (of patients)
Patient-guided use	Generate information to improve understanding of a medical condition (as a patient or as a caregiver) Virtual health assistant Clinical trial enrolment	Inaccurate, incomplete or false statements Manipulation Privacy Less interaction between clinicians and patients Epistemic injustice Risk of delivery of care outside the health system
Clerical and administrative tasks	Assist with paperwork and documentation required for clinical care Assist in language translation Completion of electronic health records Draft clinical notes after a patient visit	Inaccuracies and errors Inconsistent responses depending on prompts
Medical and nursing education	Dynamic texts suited to each student's needs Simulated conversation to improve communication and to practise in diverse situations and with diverse patients Responses to questions accompanied by chain-of-thought reasoning	Contribute to automation bias Errors or false information undermine the quality of medical education New burden of learning digital skills
Scientific research and drug development	Generate insights from scientific data and research Generate text for use in scientific articles, manuscript submission or peer-review Analyse and summarize data for research Proofreading De novo drug design	Cannot hold algorithms accountable for content Algorithms encode bias towards the perspectives of high-income countries Generate information and/or references that do not exist Undermine key tenets of scientific research, such as peer review Exacerbate differential access to scientific knowledge

Risks to health systems associated with use of LMMs in health care

Type of risk	Description
Overestimation of the benefits of LMMs	There may be a tendency to 'technological solutionism', or over-estimation of the benefits of LMMs while ignoring or downplaying challenges in its use, including its safety, efficacy and utility.
Accessibility and affordability	Equitable access to LMMs may be lacking for several reasons, including the "digital divide" and subscription fees to access LMMs.
System-wide biases	Use of ever-larger data sets could increase biases encoded in LMMs, which could be automated throughout a health-care system.
Impacts on labour	Use of LMMs could lead to job losses in some countries and require health workers to retrain and adjust to use of LMMs. Data annotation and filtering can lead to low wages and to untreated psychological distress.
Dependence of health systems on ill-suited LMMs	Dependence on LMMs could make health systems vulnerable if LMMs are not maintained or (in low- and middle-income countries) are updated only for use in high-income countries. Furthermore, lack of preservation and protection of privacy and confidentiality could undermine trust in health-care systems by people who are not confident that their privacy will be protected.
Cybersecurity risks	Malicious attacks or hacking could undermine safety and trust in the use of LMMs in health care.

WHO consensus ethical principles for use of AI for health

Protect autonomy



Promote human well-being, human safety and the public interest



Ensure transparency, explainability and intelligibility



Foster responsibility and accountability



Ensure inclusiveness and equity



Promote AI that is responsive and sustainable



Protect autonomy:

- Humans should remain in control of health-care systems and medical decisions. Providers have the information necessary to use AI systems safely and effectively.
- People understand the role that AI systems play in their care.
- Data privacy and confidentiality are protected by valid informed consent through appropriate legal frameworks for data protection.

Promote human well-being, human safety and the public interest:

- Designers of AI satisfy regulatory requirements for safety, accuracy and efficacy for well-defined uses or indications.
- Measures of quality control in practice and quality improvement in the use of AI over time should be available.
- AI is not used if it results in mental or physical harm that could be avoided by use of an alternative practice or approach.

Foster responsibility and accountability to ensure that AI is used under appropriate conditions and by appropriately trained people

- Patients and clinicians evaluate development and deployment of AI. Regulatory principles are applied upstream and downstream of the algorithm by establishing points of human supervision.
- Appropriate mechanisms are available for questioning nand for redress for individuals and groups that are adversely affected by decisions based on AI.

Ensure transparency, “explainability” and intelligibility

- AI technologies should be intelligible or understandable to developers, medical professions, patients, users and regulators.
- Sufficient information is published or documented before the design or deployment of AI, and the information facilitates meaningful public consultation and debate on how the AI is designed and how it should or should not be used.
- AI is explainable according to the capacity of those to whom it is explained.

Automated systems should be effective, and they should be tested

- Automated systems have brought about extraordinary benefits, from technology that helps farmers grow food more efficiently and computers that predict storm paths, to algorithms that can identify diseases in patients.
- It is necessary to have trust and safety teams check all automated system before their application specially in medical practice.
- Governments should create a regulatory framework and environment to make sure the safety of for AI specially in medical practice.

Ensure inclusiveness and equity

- AI is designed and shared to encourage the widest possible, appropriate, equitable use and access, irrespective of age, sex, gender identity, income, race, ethnicity, sexual orientation, ability or other characteristics.
- AI is available for use not only in high-income settings but also in low- and middle-income countries.
- AI does not encode biases to the disadvantage of identifiable groups. AI minimizes inevitable disparities in power.

Medical and nursing education

- LMMs are also projected to play a role in medical and nursing education.

- They could be used to create “dynamic texts” that, in comparison with generic texts, are tailored to the specific needs and questions of a student .

- LMMs integrated into chatbots can provide simulated conversations to improve clinician–patient communication and problem-solving.

LLM Very inconsistent as moral advisers

- LLMs such as Chat GPT may be very inconsistent as moral advisers

- Use of LMMs for moral judgments could lead to “moral de-skilling”, as physicians become unable to make difficult judgements or decisions

Medical Skills degradation

- There is a long-term risk that increased use of AI in medical practice will degrade or erode clinicians' competence as medical professionals, as they increasingly transfer routine responsibilities and duties to computers.

- Loss of skills could result in physicians being unable to overrule or challenge in daily practice

Most of today's knowledge on disease mechanisms will be forgotten

- We should realize that if this is allowed to move on, the near future will be characterized by rapidly decreasing knowledge about the pathogenesis underlying disease development.
- Once we come to a stage where output is defined in the black box that is fed by input, and this black box contains constructs that are no longer consistent with previously defined entities, most of today's knowledge on disease mechanisms will be forgotten and we will be ruled by systems that only focus on intervention strategies that will provide the best possible outcome.

Decrease in intellectual debates

- This era will show a decrease in intellectual debates among colleagues, a sign of the time that computer scientists have already warned us about.
- While authors of literature are fighting for regulations to control the usage of AI in art, physicians should contemplate how to take advantage of the potential benefits from AI in medicine without losing control over their profession

Keeping AI within boundaries

- With the issue of a landmark Executive Order in theUS to ensure that America leads the way in managing the risks of AI and the EU becoming the first continent to set clear rules for the use of AI.

- Physicians should realize that keeping AI within boundaries is essential for the survival of their profession and for meaningful progress in diagnosis and understanding of disease mechanisms.

International governance of LMMs

- Governments must work together to build new institutional structures and rules to ensure that international governance keeps pace with globalization of these technologies.
- They should also ensure stronger cooperation and collaboration within the United Nations system to respond to the opportunities and challenges for deploying AI in health care, as well as its wider applications in society and the economy

Liability for LMMs

- As LMMs gain broader use in health care and medicine, errors, misuse and ultimately harm to individuals are inevitable.
- Legal responsibility rules will have to be used to compensate individuals for such harm, with establishment of new forms of redress when current approaches are insufficient or out of date.

AI has dramatically changed the landscape of gastrointestinal endoscopy.

- The field AI in GI and Hepatology has seen almost exponential growth.
- Expectations are high that AI will revolutionize our field and significantly improve patient care.
- The field of gastroenterology and endoscopy has similarly seen a tremendous uptake in acceptance and implementation of AI for a variety of gastrointestinal conditions.
- From the first US (FDA)-approved device that uses machine learning to assist clinicians in detecting lesions during colonoscopy, to other more innovative machine learning techniques for small bowel, esophageal, and hepatobiliary conditions, AI has dramatically changed the landscape of gastrointestinal endoscopy.
- But as the global discussion on AI has shown, there are real challenges with adoption, including issues with accuracy, reliability, and privacy

AI in colorectal cancer screening

- Application of AI have been focused on procedural performance metrics, quality indicators, and tools to aid in lesion detection and improve quality of care.
- One such tool has been computer-aided detection (CADe), with early randomized controlled trial (RCT) data showing significantly increased adenoma detection rate (ADR) and adenomas per-colonoscopy (APC).
- This led to FDA approval of the computer-aided detection(CADe) system GI Genius (Medtronic, Dublin, Ireland) in 2021.

Additional systems have since been FDA approved all of which have shown increased ADR and/or increased APC and/or reduced adenoma miss rates in randomized trials

- Endoscreener (Wision AI, Shanghai China)
- SKOUT (Iterative Health, Cambridge, Massachusetts).
- MAGENTIQ-COLO (MAGENTIQ-EYE LTD, Haifa, Israel).
- CAD EYE(Fujifi lm, Tokyo),

Disconnect between FDA approved RCT data and more real-world literature

- In a recent study, no improvement was seen in ADR after implementation of a CADe system for colorectal cancer screening — including both higher and lower-ADR performers.
- Looking at change over time after implementation, CADe had no positive eff ect in any group over time, divergent from early RCT data.

Disconnect 2

- In a more recent multicenter, community-based RCT study, again CADe did not result in a statistically significant difference in the number of adenomas detected.
- The differences between some of these more recent “real-world” studies VS the majority of data from RCTs raise important questions regarding the potential of bias (due to unblinding) in prospective trials, as well as the role of the human-AI interaction

MORE AI learning CADe systems have been developed but no further FDA approval

- Early Barrett's neoplasia diagnosis,
- Depth and invasion of gastric cancer,
- Lesion detection in small bowel video capsule endoscopy.
- ERCP-based applications for cholangiocarcinoma and indeterminate stricture diagnosis.
- Improvement in endoscopic submucosal dissection (ESD) o
- Improvement in peroralendoscopic myotomy (POEM)

Artificial intelligence adoption in clinical practice

- Clinical practice with regard to AI and colorectal cancer screening largely mirrors the disconnect in the current literature, with “believers” and “non-believers” as well as innovators and early adopters alongside laggards
- More widespread adoption in community practice and larger scale real-world clinical outcomes studies are likely to determine the true impact of these exciting technologies

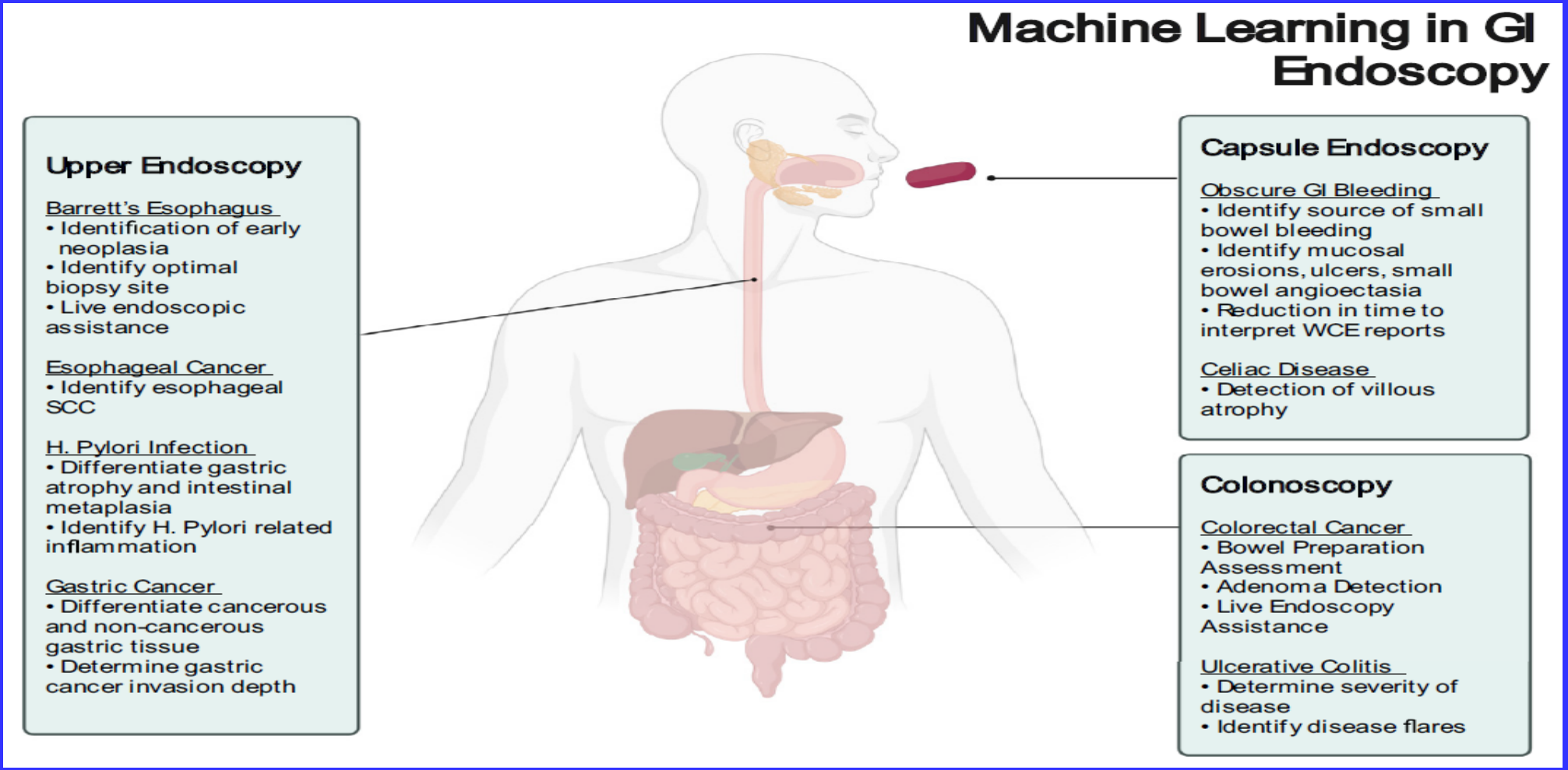
Recommendations for Government

- **Mandatory post-release auditing and impact assessments**
- **Hold providers or developers of inaccurate, false or toxic content LMM after its release**
- **Mandatory rules for developers and providers to ensure that LMMs and applications can be used safely.**
- **Deployers should let patients be aware of any risks that result from use of an LMM,**
- **MOH and UMS should train health-care professionals and clinicians a bout LMMs.**
- **Support collective development of international rules for the governance of AI**

Artificial intelligence (AI) clinical applications in gastroenterology and hepatology

- Detection of lesions,.
- Identification of premalignant or malignant lesions.
- Development of objective scoring systems for risk stratification.
- Predicting disease prognosis or treatment response.
- Evaluation of metrics such as bowel preparation score or quality of endoscopic examination.

Potential applications of artificial intelligence in GI endoscopy.



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AI and Precession Medicine

- AI applications in clinical gastroenterology and hepatology continue to rapidly expand and evolve at many different levels.
- For general clinical care, the recent proliferation in AI applications is likely to enable “precision medicine on a broader scale.
- Clinically, it is predicted that invasive diagnostic interventions will generally fall out of favor for some conditions, as better noninvasive AI-based algorithms pave the way for improved clinical prediction models

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Video capsule endoscopy (VCE)

- Some diagnostic interventions, such as VCE interpretation, may see a considerable decrease in human interpretation, minimizing the human role to that of supervision and attestation of findings of the model.
- AI-assisted technology will prove important in real-time clinical settings (e.g., polyp detection during colonoscopy).
- Integration of monitoring devices (e.g., smartphones, smart watches) with ML in the management of selected diseases is also predicted to significantly receive more attention the coming years.

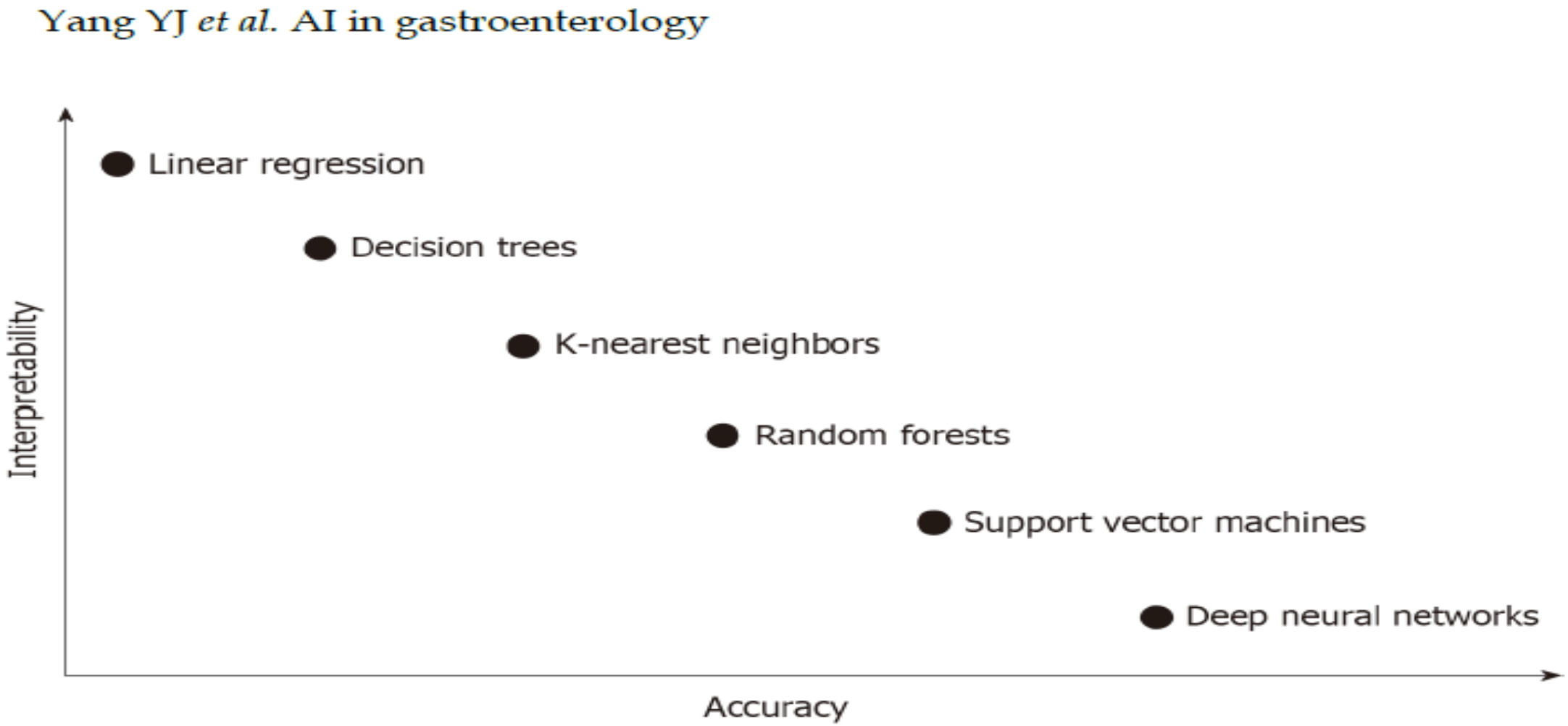
Universal, large, high-quality, well labelled dataset is essential for application of AI in Medicine

- The creation of a universal, large, high-quality, well labelled dataset is a necessity, from which algorithms could be developed to better define the epidemiology and risk factors of diseases.
- Well-harnessed AI assistance should decrease physician workload or at least maximize their productivity by allowing them to shift from menial tasks to faster, more accurate clinical decision making.
- ML algorithms based on these datasets can also be used for other quality measures, such as improvement of process efficiency or identifying cost-effective interventions.

Summary of clinical studies using artificial intelligence for recognition of diagnosis and prediction of prognosis

Ref.	Published year	Aim of study	Design of study	Number of subjects	Type of AI	Input variables (number/type)	Outcomes
Pace *et al*[11]	2005	Diagnosis of gastroesophageal reflux disease	Retrospective	159 patients (10 times cross validation)	"backpropagation" ANN	101/clinical variables	Accuracy: 100%
Lahner *et al*[12]	2005	Recognition of atrophic corpus gastritis	Retrospective	350 patients (subdivided several times into training and test set equally)	ANN	37 to 3 /clinical and biochemical variables (experiment 1 to 5)	Accuracy: 96.6%, 98.8%, 98.4%, 91.3% and 97.7% (experiment 1-5, respectively)
Pofahl *et al*[13]	1998	Prediction of length of stay for patients with acute pancreatitis	Retrospective	195 patients (training set: 156, test set: 39)	"backpropagation" ANN	71/clinical variables	Sensitivity: 75 % (for prediction of a length of stay more than 7 d)
Das *et al*[14]	2003	Prediction of outcomes in acute lower gastrointestinal bleeding	Prospective	190 patients (training set: 120, internal validation set: 70, external validation set: 142)	ANN	26/clinical variables	Accuracy (external validation set): 97% for death, 93% for, recurrent bleeding, 94% for need for intervention

Interpretability-accuracy tradeoff in classification algorithms of machine learning



Future Directions for AI in Computer Vision Endoscopy

Problem	ML solution
Classification of esophageal varices and risk stratification	Agreement among endoscopists varies widely regarding size of esophageal varices. Automated stratification and risk classification could significantly impact practice and provide endoscopists with a tool to more accurately define varices.[62]
Differentiation of ulcerative colitis vs Crohn's disease	Distinction between ulcerative colitis and Crohn's disease can be challenging endoscopically as well as histologically.[63,64] Numerous scoring tools have been created to assist endoscopists in diagnosis; however, this problem lends itself well to ML assistance in the future.
Assessment of biliary strictures during ERCP	The differentiation between benign and malignant biliary strictures during ERCP is challenging even for the most advanced endoscopists, and it is possible that ML could help identify features associated with benign and malignant disease that could assist the endoscopist.[65]
Predicting bile duct cannulation difficulty	One of the most challenging aspects of ERCP is determining the likelihood of success in achieving bile duct cannulation, and thus presents another opportunity for ML assistance to transform practice.[65]
Quality assessment of mucosal inspection	ML could not only assist with training of endoscopists but also provide real-time feedback regarding the percent of mucosa examined during EGD or colonoscopy to ensure adequate examination is taking place.[66]
Standardized training in endoscopy	ML-developed systems can likely help standardize the training and assessment of fellows in the development of endoscopy skills.[10]

EGD, esophagogastroduodenoscopy; ERCP, endoscopic retrogradecholangiopancreatography.

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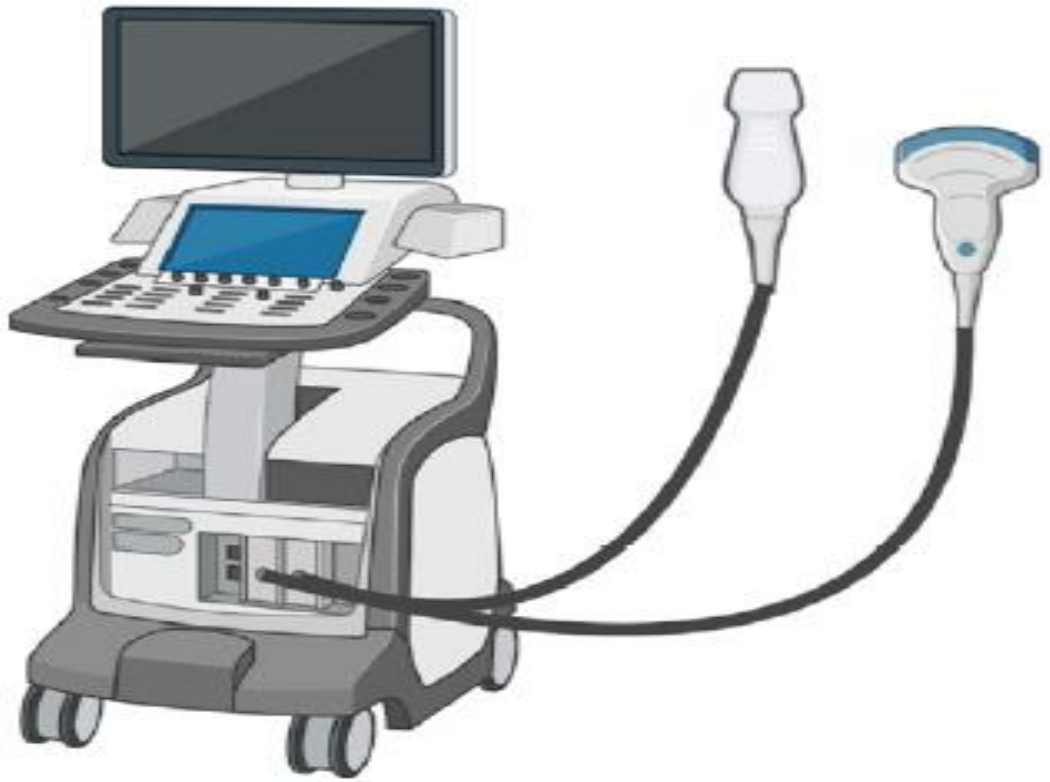
Potential applications of artificial intelligence in GI radiology.

Hepatology

- Identification of liver disease
- Determine fibrosis stage
- Identify Liver Lesions
- Differentiate benign vs malignant lesions



Pancreatology

- Identification of intraductal papillary mucinous neoplasms
- Identification and staging of pancreatic cancer
- Diagnosis of pancreatic ductal adenocarcinoma
- Quantify degree of intrapancreatic fat

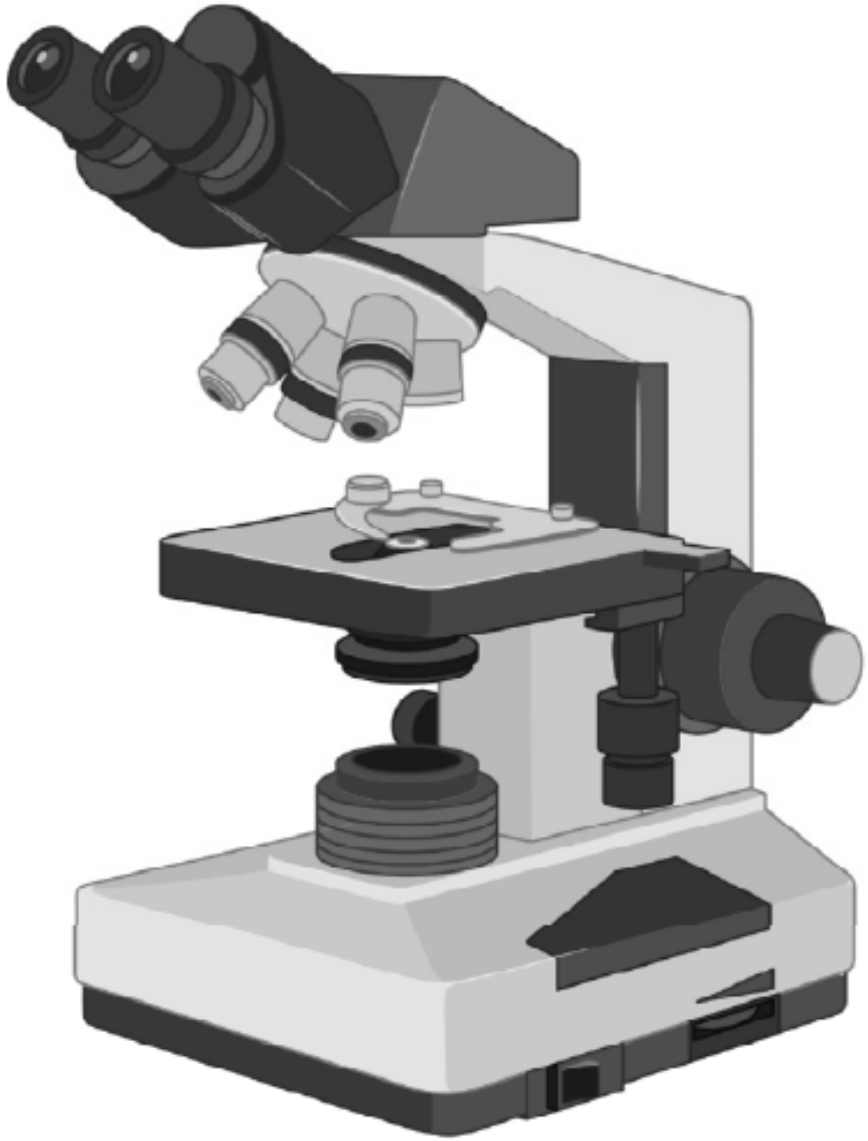
Machine Learning in GI Pathology

Luminal GI

- Diagosis of Celiac Disease
- Classify Colorectal Polyps
- Diagnosis of Barrett's Esophagus

Hepatology

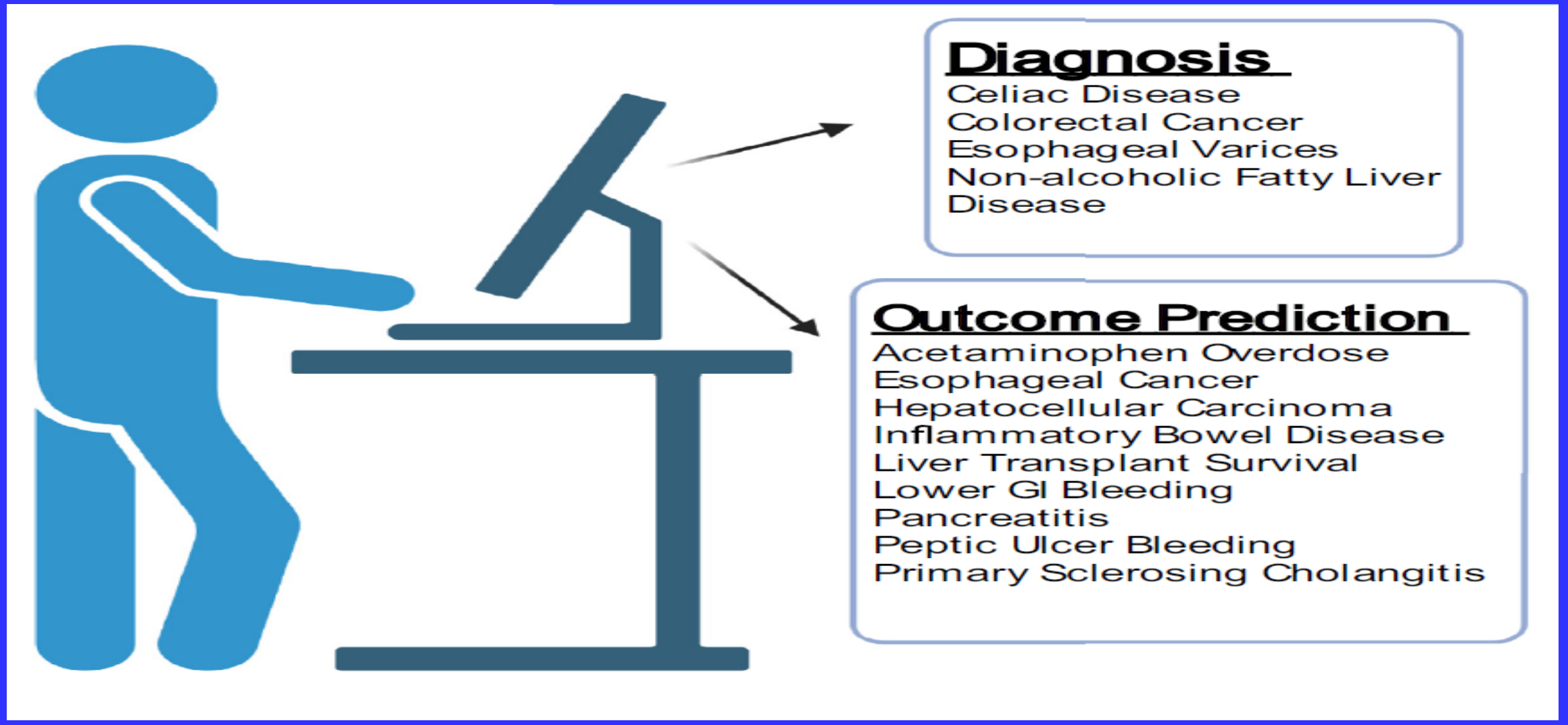
- Diagnosis of NAFLD and NASH
- Identification of NAFLD
- Identification of specific histologic features such as macrosteatosis
- Determine degree of fibrosis
- Predict treatment response in NASH



GI Malignancy

- Survival prediction in colorectal cancer
- Identification of microsatellite instability
- Identification of Esophageal Adenocarcinoma
- Differentiation between HCC and Cholangiocarcinoma
- Predict prognosis and survival in HCC

Machine Learning in GI Electronic Health Record Data



Future impact of artificial intelligence on the practice of gastroenterology and hepatology







Post- Hospital Care

- Post-hospital dicharge vital sign monitoring
- Remote monitoring of labs, such as hemoglobin after endoscopy
- Monitor voice patterns for signs of hepatic encephalopathy

Virtual GI Clinic

- Virtual clinic visits
- Home based diagnostic testing (ascites measurements, virtual capsule endoscopy)
- Virtual Reality therapies for functional disorders

Educating Scientists ,clinicians and patients in the future paths of AI

- In terms of data analysis, traditional analytic models (e.g., logistic regression and clinical scoring systems) may be substituted or augmented by ML algorithms to achieve greater capability and accuracy.
- Developing and maintaining multidisciplinary teams of data scientists, physicians, content subject experts and industry is of paramount importance in the advancement of AI in gastroenterology and hepatology.
- Finally, educating clinicians and patients in the future paths of AI applications is critical to increase understanding of future value and decrease reluctance in engagement

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Main Research Gaps Still to Be Investigated for Artificial Intelligence in the Field of GI and Hepatology

Main research gaps
Variations in performance levels of AI due to:
Lack of high-quality datasets for ML development and great heterogeneity in the size of training and testing datasets
Wide variety of performance metrics (accuracy, sensitivity, specificity, precision, F1 score, and AUROC)
Lack of validation techniques in multiple studies
Lack of randomized controlled trials comparing AI-assisted approaches to current non–AI-based approaches:
Only 2 published RCTs up to date, most evidence used to develop ML algorithms coming from preclinical studies
Limitations of AI techniques that require further investigation:
"Black-box models" preventing physicians from finding potential confounding factors
Ethical challenges
Inherent biases
Multiple other areas outside the field of diagnosis and prognosis assistance are still under-investigated:
Quality metrics for gastrointestinal endoscopy
Bedside computer vision especially in intensive care units
Therapeutic advances particularly in immunotherapy

RCT, randomized controlled trial.

Conclusions

- In Future that AI 3.0 will come into practice as augmentation tools,
- Initially helping with aspects of health care such as documentation burden.
- As these tools subsequently begin to support clinical practice, with clinicians in the loop..
- A thoughtful regulatory framework will be needed for AI that is outcome-centric by requiring companies to demonstrate that AI tools produce clinically important differences in patient outcomes before being brought to market.