Public Health Digitalization in Europe

Room and Scope for AI to Support Public Health Values the case of infectious diseases

Prof. Anna Odone, MD PhD
European Public Health Association
University of Pavia

EUPHA

EUROPEAN PUBLIC HEALTH ASSOCIATION

Digital Health and Artificial Intelligence

Empowering public health in the age of AI and data

An umbrella organization for public health associations and institutes in Europe. EUPHA now has 86 members from 47 countries, bringing together around 25’000 public health experts for professional exchange and collaboration throughout Europe

Chaired by

Martin McKee Walter Ricciardi

EPH PUBLIC HEALTH CONFERENCE

I'M SPEAKING AT THE ROUNDTABLE

The Digital Transformation of Healthcare in Europe

THURSDAY 29th - 9am to 10.30am

Linhart Hall

#EPH2018

European Journal of Public Health, Vol. 29, Supplement 3, 28–35

doi:10.1093/eurpub/ckz161

Public health digitalization in Europe

EUPHA vision, action and role in digital public health

Anna Odone[1,2], Stefan Buttigieg[2,3], Walter Ricciardi[2,4], Natasha Azzopardi-Muscat[2,5], Anthony Staines[6]

1 School of Public Health, Faculty of Medicine, University Vita-Salute San Raffaele, Milan, Italy
2 European Public Health Association, Utrecht, The Netherlands
3 Digital Health Malta, Villetta, Malta
4 Sezione di Igiene, Istituto di Sanità Pubblica, Università Cattolica del Sacro Cuore, Rome, Italy
5 Department of Health Services Management, Faculty of Health Science, University of Malta, Villetta, Malta
6 School of Nursing and Human Sciences, Dublin City University, Dublin 9, Ireland

Correspondence: Anna Odone, School of Public Health, Faculty of Medicine, University Vita-Salute San Raffaele, Via Olgettina, 58, 20132 Milano, Italy, Tel: +39 02 26435525, Fax: 02 2643 3375, e-mail: odone.anna@hsr.it

Volume 29, Issue Supplement_3
October 2019

Digitalization as a means, not an end in itself

Founding principle

Digitalization should not modify public health principles; rather it should support and enable their implementation […] Digital public health is therefore not a discipline per se but an ***asset our community has to fulfil its aims and mission****. The health system goals of* ***quality, accessibility, efficiency and equity of healthcare, embraced by public health professionals are unaltered by the process of digitalization***

Conceptual framework 1/2

Public health Pillars	Public health Domains	Digital Health Technologies[a]
Practice Research Training and Education Policy	Health prevention Health communication Health education Health promotion Health services organization, management and delivery Epidemiology and control of communicable diseases Risk management, hospital hygiene and safety Epidemiology and control of non-communicable diseases Food safety Environmental health Surveillance analysis and reporting Impact assessment monitoring and evaluation	Genomics Telehealth Smartphone apps (MHEALTH) Social media Wearables and sensors Virtual and augmented reality Drones Internet of things Big data Artificial intelligence (incl. predictive analytics, speech recognition and natural language processing) Robotics Distributed ledger technologies

The Added Value Of Digitalization For Public Health: **Digital features which bolster public health action**

- Personalization and precision
- Automation
- Prediction
- Data analytics
- Interaction

Conceptual framework 2/2

Table 1 The potential added value of digitalization for public health: a conceptual framework

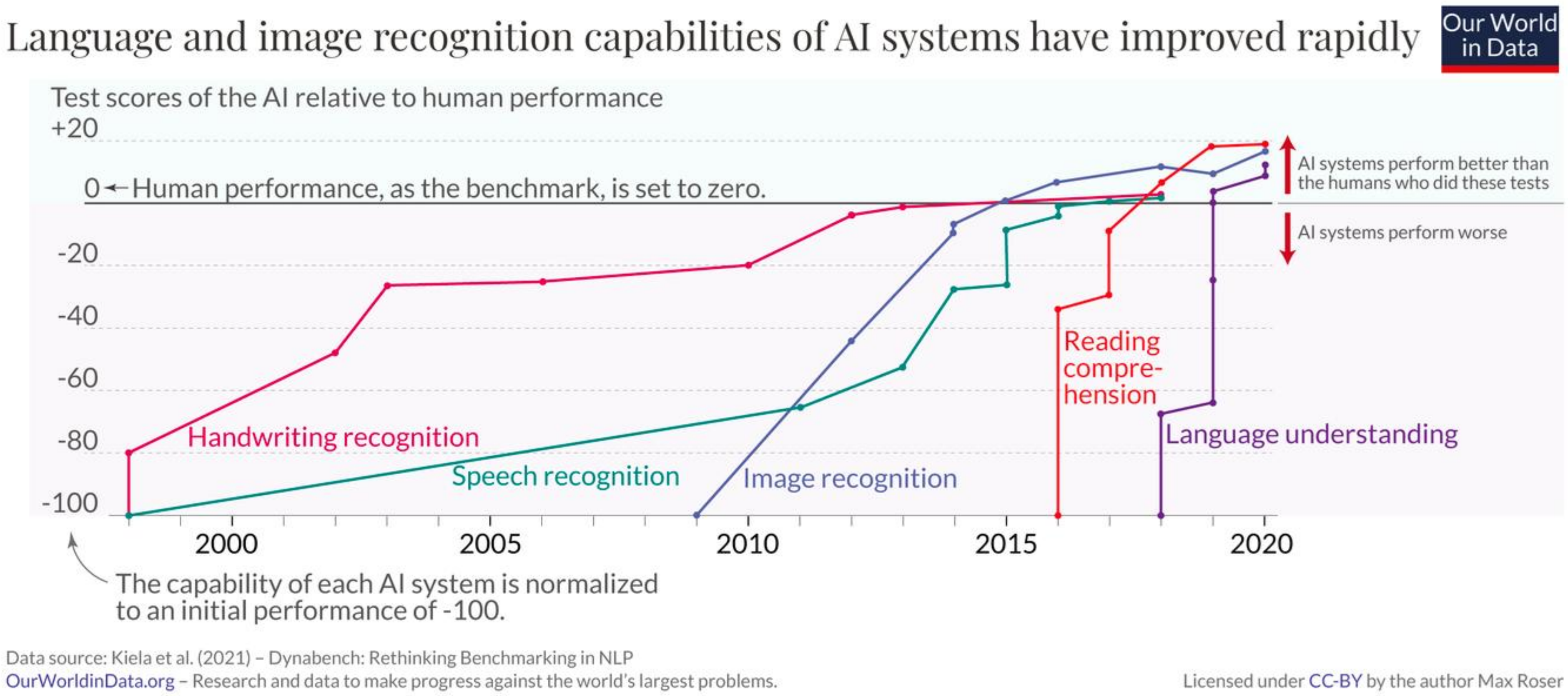
Public health Pillars	Public health Domains	Digital Health Technologies[a]	Features	Potential Public health Benefits and advantages
Practice Research Training and Education Policy	Health prevention Health communication Health education Health promotion Health services organization, management and delivery Epidemiology and control of communicable diseases Risk management, hospital hygiene and safety Epidemiology and control of non-communicable diseases Food safety Environmental health Surveillance analysis and reporting Impact assessment monitoring and evaluation	Genomics Telehealth Smartphone apps (MHEALTH) Social media Wearables and sensors Virtual and augmented reality Drones Internet of things Big data Artificial intelligence (incl. predictive analytics, speech recognition and natural language processing) Robotics Distributed ledger technologies	Personalization and Precision Automation Prediction Data analytics (incl. Big Data, data transfer and interoperability) Interaction	Shift from cure to prevention Care closer to people People-centered care Safer, faster and more efficient services Less expensive care

Box 1 Potential Public health benefits and advantages brought by digitalization

From a public health perspective, digitalization provides several benefits:

- It supports the transition from cure to prevention
- It helps to put people and patients at the center and supports their empowerment;
- It makes healthcare management and delivery more efficient, safer and cheaper

A rapidly changing landscape of technologies…



Max Roser (2022) - "The brief history of artificial intelligence: The world has changed fast – what might be next?" Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/brief-history-of-ai'

A rapidly changing landscape of medical applications…

A digital health algorithm to guide antibiotic prescription in pediatric outpatient care: a cluster randomized controlled trial

Hand hygiene monitoring and compliance system using convolution neural networks

Anubha Nagar[1] · Mithra Anand Kumar[1] · Naveen Kumar Vaegae[1]

COMMENT | VOLUME 5, ISSUE 3, E107-E108, MARCH 2023

ChatGPT: the future of discharge summaries?

Machine learning based refined differential gene expression analysis of pediatric sepsis

Mostafa Abbas & Yasser EL-Manzalawy

Nature 2022

Automated healthcare-associated infection surveillance using an artificial intelligence algorithm

R.P. dos Santos,[a] D. Silva,[a,*] A. Menezes,[a] S. Lukasewicz,[a] C.H. Dalmora,[a] O. Carvalho,[a] J. Giacomazzi,[b] N. Golin,[b] R. Pozza,[b] and T.A. Vaz[a]

Using artificial intelligence to reduce orthopedic surgical site infection surveillance workload: Algorithm design, validation, and implementation in 4 Spanish hospitals

Álvaro Flores-Balado MD[a], Carlos Castresana Méndez[b], Antonio Herrero González[c], Raúl Mesón Gut … D[d], Javier Arcos MD …

Article

Discovery of a structural class of antibiotics with explainable deep learning

https://doi.org/10.1038/s41586-023-06887-8

Received: 5 January 2022

Accepted: 21 November 2023

Published online: 20 December 2023

Felix Wong[1,2,3,10], Erica J. Zheng[1,4,5,10], Jacqueline A. Valeri[1,2,5], Nina M. Donghia[5], Melis N. Anahtar[1], Satotaka Omori[1,3], Alicia Li[3], Andres Cubillos-Ruiz[1,2,5], Aarti Krishnan[1,2], Wengong Jin[6], Abigail L. Manson[1], Jens Friedrichs[7], Ralf Helbig[7], Behnoush Hajian[8], Dawid K. Fiejtek[8], Florence F. Wagner[8], Holly H. Soutter[8], Ashlee M. Earl[1], Jonathan M. Stokes[1,2,9], Lars D. Renner[7] & James J. Collins[1,2,5]

Can natural language processing provide accurate, automated reporting of wound infection requiring reoperation after lumbar discectomy?

Aditya V. Karhade, BE[a], Michiel E.R. Bongers, MD[a], Olivier Q. Groot, MD[a], Thomas D. Cha, MD, MBA[a,b], Terence P. Doorly, MD[c], Harold A. Fogel, MD[a,b], Stuart H. Hershman, MD[a], Daniel G. Tobert, MD[a,b], Andrew J. Schoenfeld, MS, MSc[d,e], James D. Kang, MD[d,e], Mitchel B. Harris, MD[a], Christopher M. Bono, MD[a], Joseph H. Schwab, MD, MS[a,b,*]

Infection Control & Hospital Epidemiology (2023), 44, 1776–1781
doi:10.1017/ice.2023.54

Original Article

Clostridioides difficile infection surveillance in intensive care units and oncology wards using machine learning

Erkin Ötleş MS[1,2], Emily A. Balczewski BA[1,3], Micah Keidan BS[4], Jeeheh Oh PhD[5], Alieysa Patel MPH[6], Vincent B. Young MD, PhD[4,7], Krishna Rao MD, MS[4] and Jenna Wiens PhD[5]

[1]Medical Scientist Training Program, University of Michigan Medical School, Ann Arbor, Michigan, [2]Department of Industrial & Operations Engineering, College of Engineering, University of Michigan, Ann Arbor, Michigan, [3]Department of Computational Medicine and Bioinformatics, University of Michigan, Ann Arbor, Michigan, [4]Division of Infectious Diseases, Department of Internal Medicine, University of Michigan Medical School, Ann Arbor, Michigan, [5]Department of Electrical Engineering and Computer Science, College of Engineering, University of Michigan, Ann Arbor, Michigan, [6]Department of Pathology, University of Michigan Medical School, Ann Arbor, Michigan and [7]Department of Microbiology and Immunology, University of Michigan Medical School, Ann Arbor, Michigan

UNIVERSITÀ DI PAVIA

Artificial intelligence in public health: promises, challenges, and an agenda for policy makers and public health institutions

Dimitra Panteli, Keyrellous Adib, Stefan Buttigieg, Francisco Goiana-da-Silva, Katharina Ladewig, Natasha Azzopardi-Muscat, Josep Figueras, David Novillo-Ortiz, Martin McKee

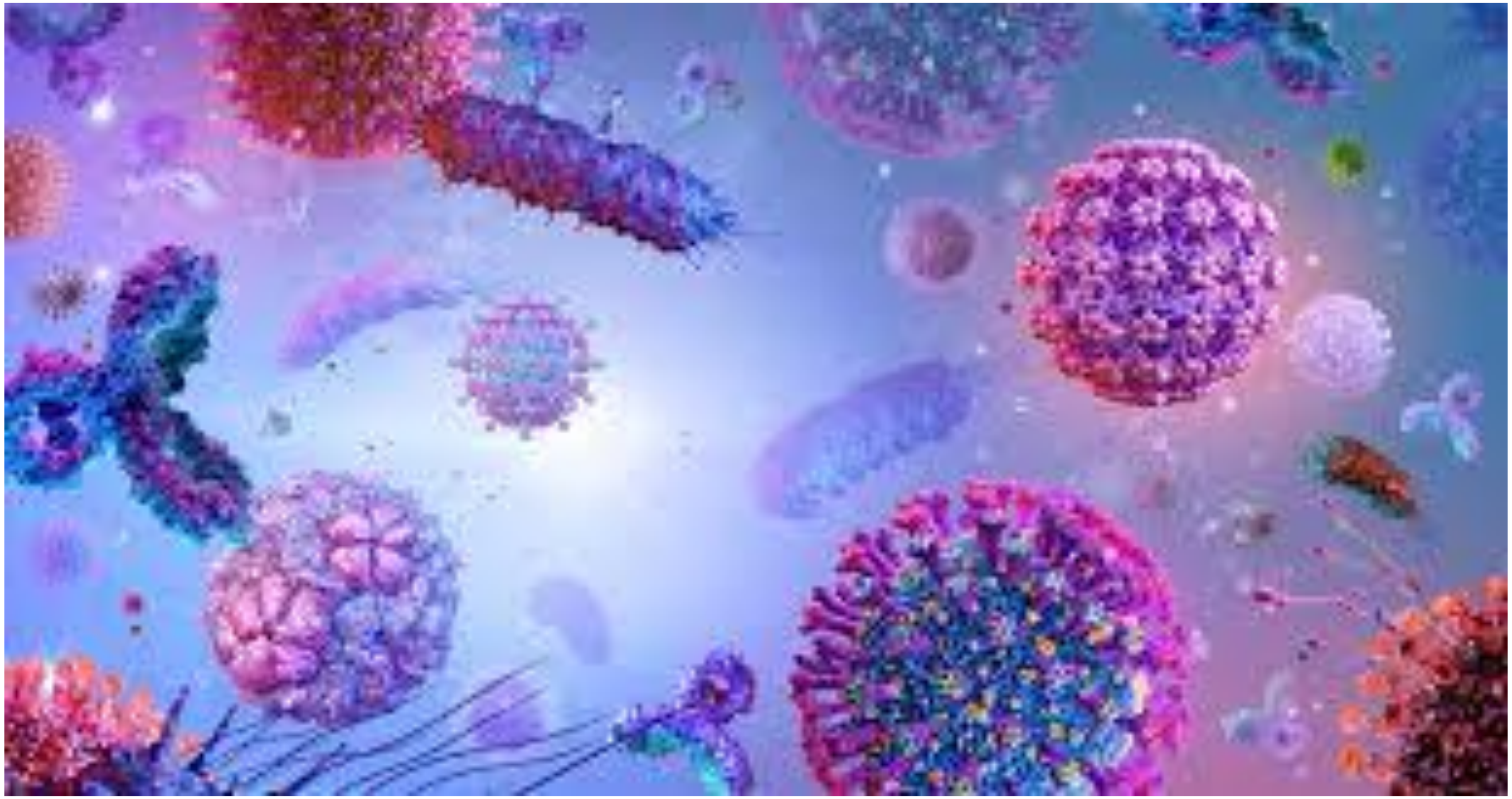
Artificial intelligence (AI) can rapidly analyse large and complex datasets, extract tailored recommendations, support decision making, and improve the efficiency of many tasks that involve the processing of data, text, or images. As such, AI has the potential to revolutionise public health practice and research, but accompanying challenges need to be addressed. AI can be used to support public health surveillance, epidemiological research, communication, the allocation of resources, and other forms of decision making. It can also improve productivity in daily public health work. Core challenges to its widespread adoption span equity, accountability, data privacy, the need for robust digital infrastructures, and workforce skills. Policy makers must acknowledge that robust regulatory frameworks covering the lifecycle of relevant technologies are needed, alongside sustained investment in infrastructure and workforce development. Public health institutions can play a key part in advancing the meaningful use of AI in public health by ensuring their staff are up to date regarding existing regulatory provisions and ethical principles for the development and use of AI technologies, thinking about how to prioritise equity in AI design and implementation, investing in systems that can securely process the large volumes of data needed for AI applications and in data governance and cybersecurity, promoting the ethical use of AI through clear guidelines that align with human rights and the public good, and considering AI's environmental impact.

Lancet Public Health 2025; 10: e428–32

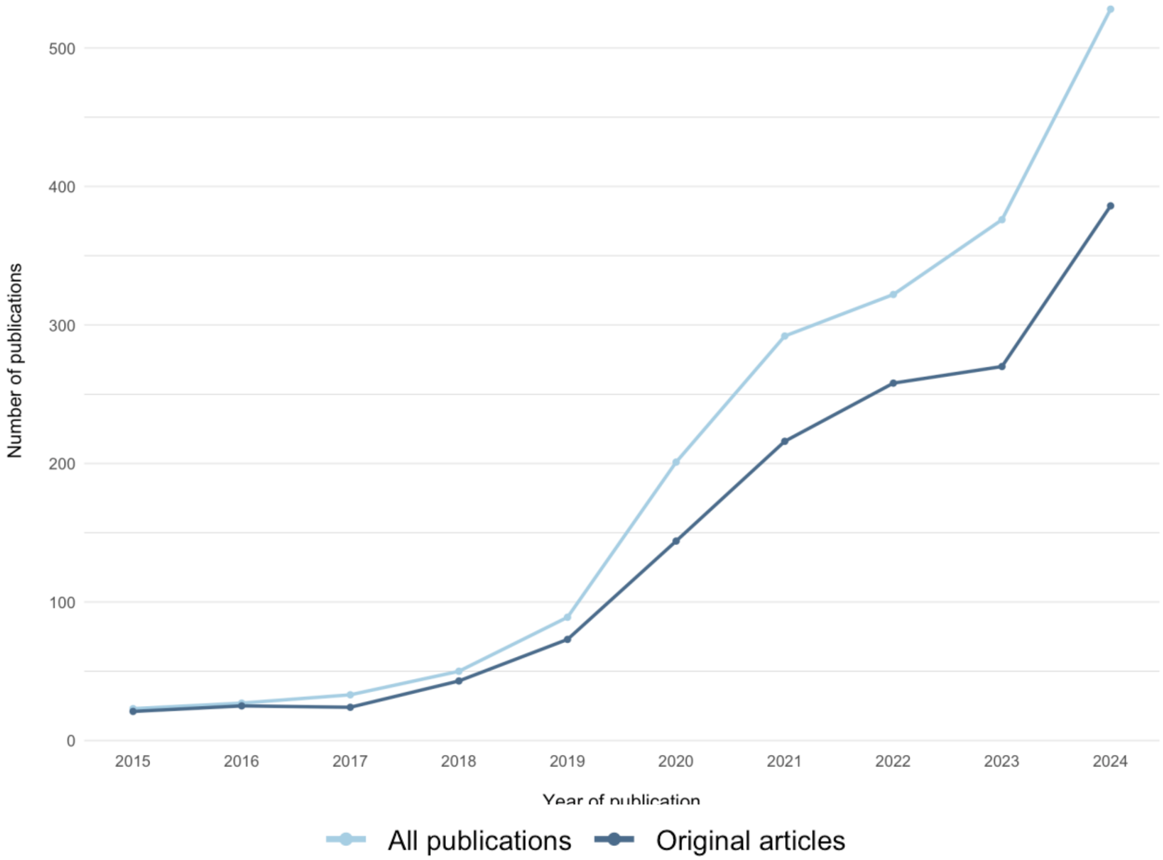
Published Online
February 28, 2025
https://doi.org/10.1016/
S2468-2667(25)00036-2

European Observatory on Health Systems and Policies, Brussels, Belgium (D Panteli DrPH, J Figueras PhD, Prof M McKee DSc); **WHO Regional Office for Europe, UN City, Copenhagen, Denmark** (K Adib MPH, N Azzopardi-Muscat PhD, D Novillo-Ortiz PhD); **Ministry**

The case of infectious diseases



A rapidly changing landscape of papers



- Over 2,000 articles on AI and infectious diseases were published between 2015 and 2025 (~25% of them are non-primary studies).
- Steep increase in volumes starting from 2018-2019

Source: Odone et al, LID 2025

THE LANCET
Infectious Diseases

SERIES | GLOBAL HEALTH | CLINICAL

Artificial Intelligence and Infectious Diseases

Published: September 16, 2025

Executive summary

As artificial intelligence (AI) use in health care evolves, its potential to support infectious disease prevention and management, from clinical care to outbreak detection and infection control, is attracting attention. However, AI adoption remains uneven, hindered by fragmented data, regulatory challenges, and low literacy and trust among professionals.

This Series aims to support the infectious disease community in understanding this evolving landscape and shaping AI integration into practice. The first review outlines a conceptual framework that draws on available AI models and data sources across pathogens, hosts, and the environment to identify domains where AI can be applied in infectious disease research, public health, and clinical practice. The second review explores AI use in diagnostics, covering pathogen identification, laboratory workflows, and antimicrobial stewardship. The third review examines AI's role in tackling antimicrobial resistance, spanning decision support, surveillance systems, and antibiotic discovery.

Rationale – Lancet series on AI and IDs

- As artificial intelligence use in health care evolves, its potential to support infectious disease prevention and management, from clinical care to outbreak detection and infection control, is attracting attention
- However, AI adoption remains uneven, hindered by fragmented data, regulatory challenges, and low literacy and trust among professionals

This Series aims to support the infectious disease community in understanding this evolving landscape and shaping AI integration into practice

The Lancet Infectious Diseases Series on Artificial Intelligence and Infectious Diseases

Artificial intelligence (AI) offers promising opportunities to help tackle infectious disease threats by improving clinical management, outbreak detection, and infection control.

This Series paper proposes a conceptual framework to map the layers and domains where AI solutions can be applied to infectious disease prevention and management across clinical practice, research, and public health. However, data availability, technical, regulatory, ethical and cultural barriers, skepticism, and lack of training among infectious disease professionals still limit the translation of AI's potential into practice.

Published 16 September 2025

Series

Artificial intelligence and infectious diseases: an evidence-driven conceptual framework for research, public health, and clinical practice
Anna Odone, Chiara Barbati, Silvia Amadasi, Tanja Schultz, David B Resnik
The Lancet Infectious Diseases

Artificial intelligence and infectious disease diagnostics: state of the art and future perspectives
Luca Miglietta, Timothy M Rawson, Ronald Galiwango, Alex Tasker, Damien K Ming, Darlington Akogo, et al.
The Lancet Infectious Diseases

Artificial intelligence and infectious diseases: tackling antimicrobial resistance, from personalised care to antibiotic discovery
Alex Howard, Nada Reza, Peter L Green, Mo Yin, Erin Duffy, Henry C Mwandumba, et al.
The Lancet Infectious Diseases

Comments

Artificial intelligence in the development of vaccines for infectious diseases
Steve Black, Shabir A Madhi, Rino Rappuoli
The Lancet Infectious Diseases

Artificial intelligence and One Health: potential for spillover prediction?
Marion Koopmans, Istvan Csabai, Daniel Remondini, Emma Snary, Frank Aarestrup
The Lancet Infectious Diseases

Solving the data bottleneck for artificial intelligence in infectious diseases
Cesar de la Fuente-Nunez
The Lancet Infectious Diseases

Podcast

In conversation with... Anna Odone, Jesus Rodriguez-Bano, and Alex Howard

Series authors discuss their papers on artificial intelligence and infectious diseases intended to support the infectious diseases community in understanding this evolving landscape.

0:00 / 0:00

https://www.thelancet.com/series-do/artificial-intelligence-and-infectious-diseases

What's needed:

a framework to comprehensively assess the areas in infectious disease prevention and management where AI can be applied successfully

THE LANCET
Infectious Diseases

Artificial Intelligence and Infectious Diseases 1

Artificial intelligence and infectious disease: an evidence-driven conceptual framework for research, public health, and clinical practice

Anna Odone, Chiara Barbati*, Silvia Amadasi, Tanja Schultz, David B Resnik*

As artificial intelligence (AI) is projected to radically shape health care, its role in infectious disease prevention and management is drawing attention. AI offers promising opportunities to help tackle infectious disease threats and improve clinical management, outbreak detection, and infection control. As part of a dedicated Series on AI and infectious diseases, this paper sets the scene by proposing a conceptual framework that, building upon available AI models and data sources related to pathogens, human hosts, and the environment, comprehensively identifies selected domains where AI can be applied across infectious disease research, public health, and clinical practice. Building on this foundation, the two companion papers in the Series follow with an in-depth exploration of AI applications in diagnostics and antimicrobial resistance. We provide an overview of current and future applications of AI in infectious disease prevention and management, exploring the broad potential, available experimental evidence, real-life implementation examples, and technical normative, ethical, and policy barriers.

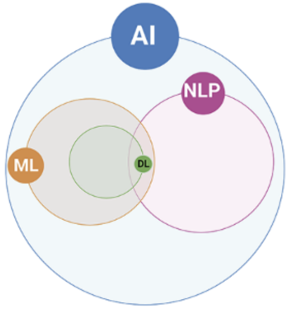
Lancet Infect Dis 2025
Published Online
Month date, 2025
https://doi.org/10.1016/S1473-3099(25)00412-8

See Online/XXX
https://doi.org/10.1016/PII

This is the first in a Series of three papers about artificial intelligence and infectious diseases. All papers in the Series are available at thelancet.com/series/XXXX

UNIVERSITÀ DI PAVIA

1) AI solution lifecycle



- AI is a broad field that includes anything related to making machines smart.
- NLP is the branch of AI focused on teaching machines to understand, interpret, and generate human language.
- ML is a subset of AI that involves systems that can learn by themselves.
- DL is a subset of ML that uses models built on deep neural networks to detect patterns with minimal human involvement.

Tracing the Evolution of AI with a Better Understanding of the Relationship Between AI, ML, DL, and NLP From: Alowais et al. BMC Medical Education https://doi.org/10.1186/s12909-023-04698-z (2023) 23:689

Figure 1: **Steps of the AI solution lifecycle and associated barriers**

www.thelancet.com/infection **Published online September 16, 2025 https://doi.org/10.1016/S1473-3099(25)00412-8**

Data collection and preprocessing

Data collection and preprocessing might vary in **format** (eg, unstructured text, structured data, and images) and in **collection methods** (at the individual level, eg, electronic health records, or at the population level (eg, epidemiological surveillance data; table 1).[19,37]

AI model development and technical validation

AI model development and technical validation involves the selection of appropriate AI techniques and methodologies, depending on **data format** (eg, deep learning for image processing and natural language processing for unstructured text), the **distribution** of available data (eg, applying class imbalance strategies when datasets contain few infected cases compared to controls, or selecting appropriate validation methods), and the **specific task** in infectious disease prevention and management (eg, classification for infection prediction or text extraction for clinical note processing). Model performance is then assessed during technical validation using adequate **performance metrics**, depending on model type and tasks (eg, accuracy, sensitivity, and AUROC).[38]

Clinical validation and deployment

Clinical validation and deployment of AI models can take place at different levels. According to previous definitions, **clinical validation** refers to testing an AI solution with real patient data to assess its safety and effectiveness. This includes **retrospective validation** (testing the AI solutions before they are implemented in patient care or using data collected before the start of the study), **prospective validation** (testing the device after it is implemented in patient care or using data collected after the start of the study), and, in its most rigorous and preferred form, **experimental studies** (ie, RCTs).[39]

Adoption and continuous monitoring

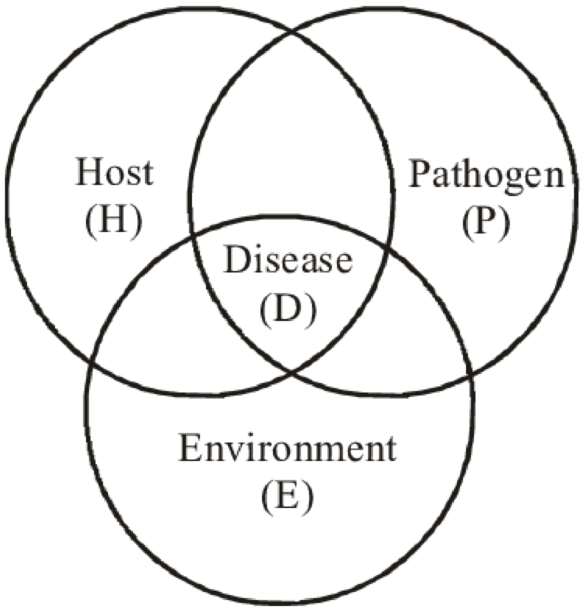
Adoption and continuous monitoring of AI solutions requires **training and building trust** among health-care professionals, and also ongoing regulations, guidelines and surveillance systems to monitor the performance of AI models and **update** them according to new clinical and technological evidence.

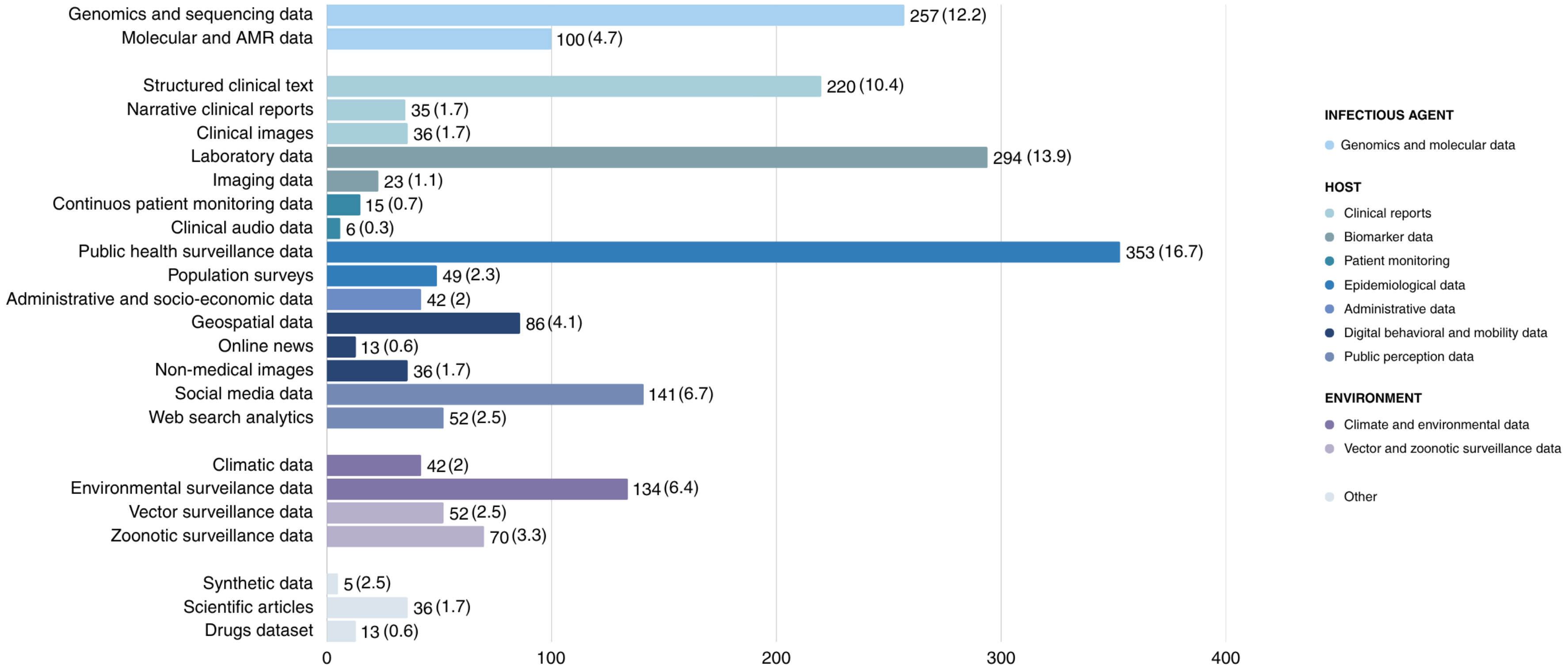
Scaling infrastructure and policy implementation

Scaling of **infrastructure** and **policy implementation** for the adoption AI solutions at the local, national, or global level depends on appropriate policies, including **investment** in technological infrastructure, **interoperability** with existing health-care systems, and strategies to ensure **equitable** access and long-term **sustainability**.[40]

2) data sources

Data sources to train AI models (the first step of their lifecycle) are multiple and have been categorised according to the epidemiological triad – pathogens, human hosts, environment





UNIVERSITÀ DI PAVIA

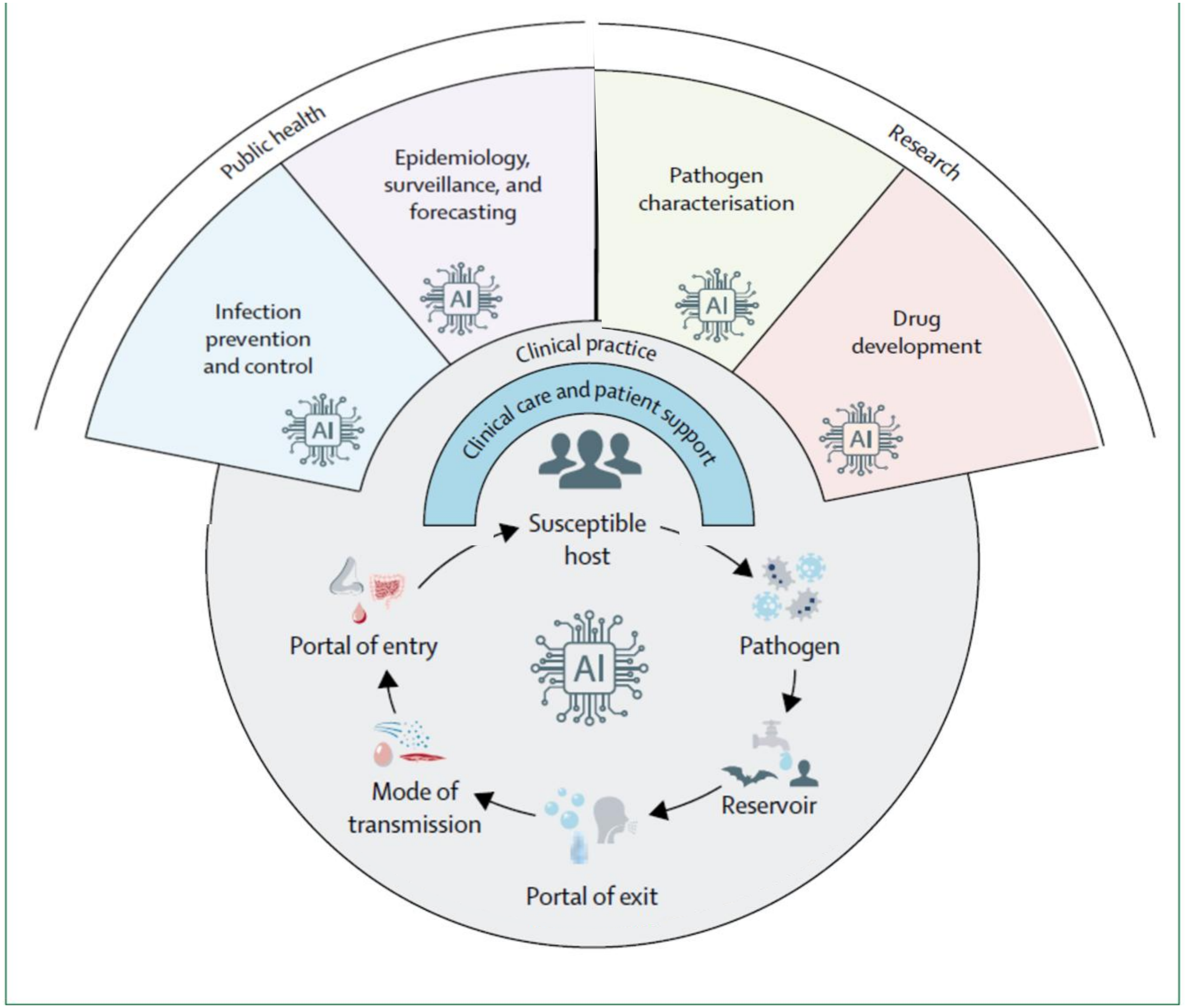
The framework: map all potential AI applications in infectious disease prevention and management

Core → layers functionally oriented around the chain of infection model

First layer → Clinical practice
Domain:
- Clinical care and patient support

Second layer → Research
Domains:
- Pathogen characterization
- Drug Development

Third layer → Public Health
Domains:
- Epidemiology, surveillance and forecasting
- Infection prevention and control

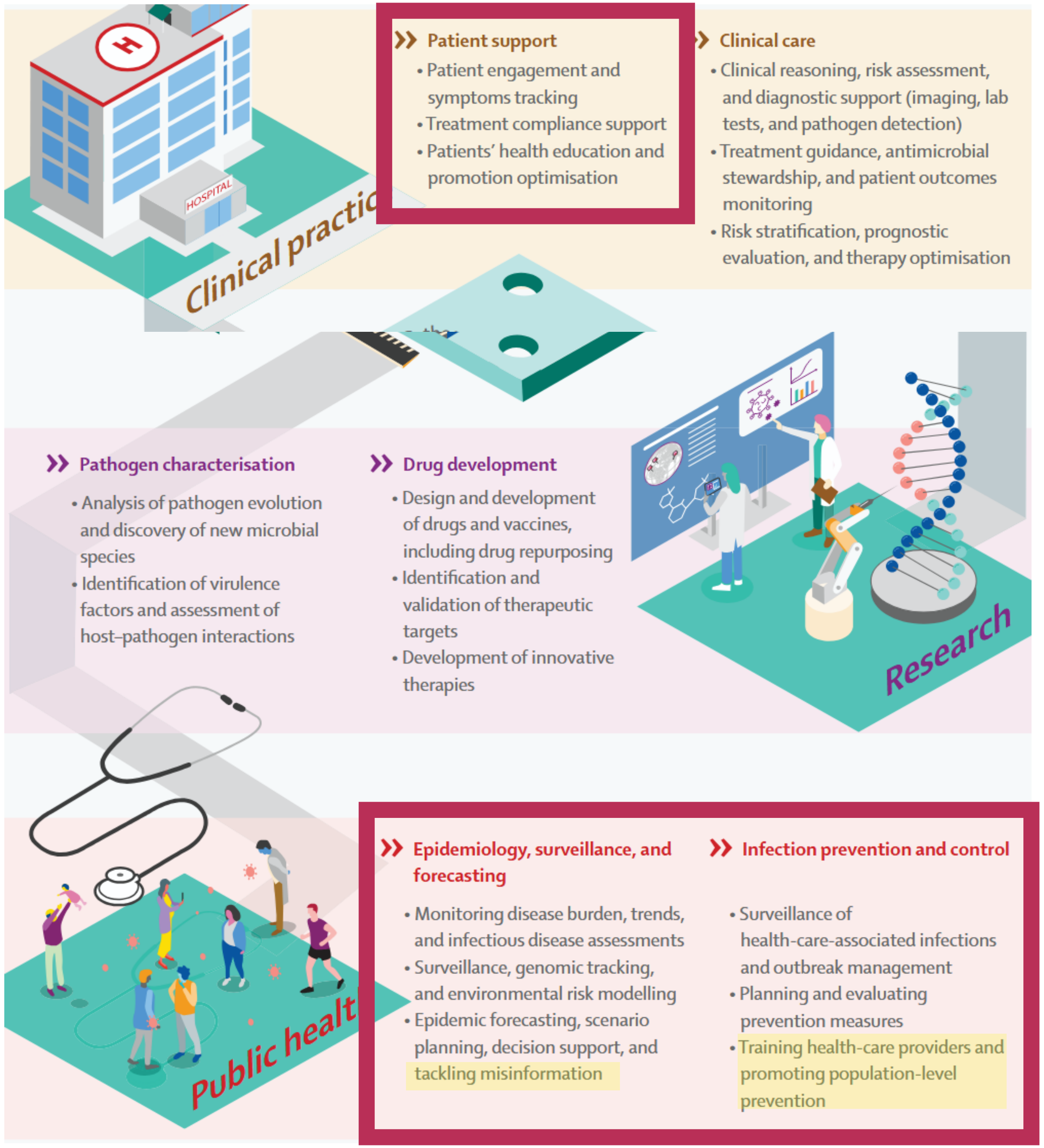


Layers and domains of AI application described by the framwork

The Lancet Infectious Diseases Series on Artificial Intelligence and Infectious Diseases

Artificial intelligence (AI) offers promising opportunities to help tackle infectious disease threats by improving clinical management, outbreak detection, and infection control.

This Series paper proposes a conceptual framework to map the layers and domains where AI solutions can be applied to infectious disease prevention and management across clinical practice, research, and public health. However, data availability, technical, regulatory, ethical and cultural barriers, skepticism, and lack of training among infectious disease professionals still limit the translation of AI's potential into practice.

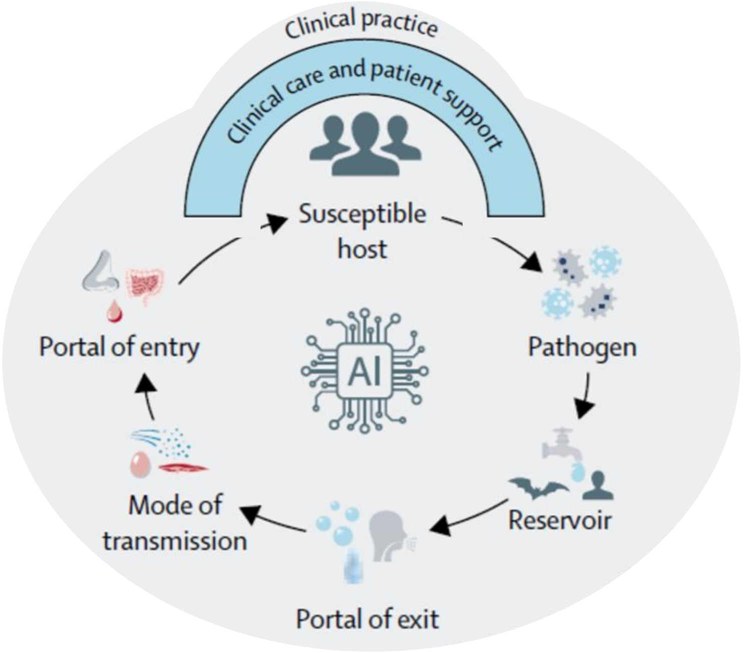


Clinical Practice

First layer → Clinical practice
Domain:
- Clinical care and patient support

Patient support
- Patient engagement and symptoms tracking
- Treatment compliance support
- Patients' health education and promotion optimisation

Clinical care
- Clinical reasoning, risk assessment, and diagnostic support (imaging, lab tests, and pathogen detection)
- Treatment guidance, antimicrobial stewardship, and patient outcomes monitoring
- Risk stratification, prognostic evaluation, and therapy optimisation



Research

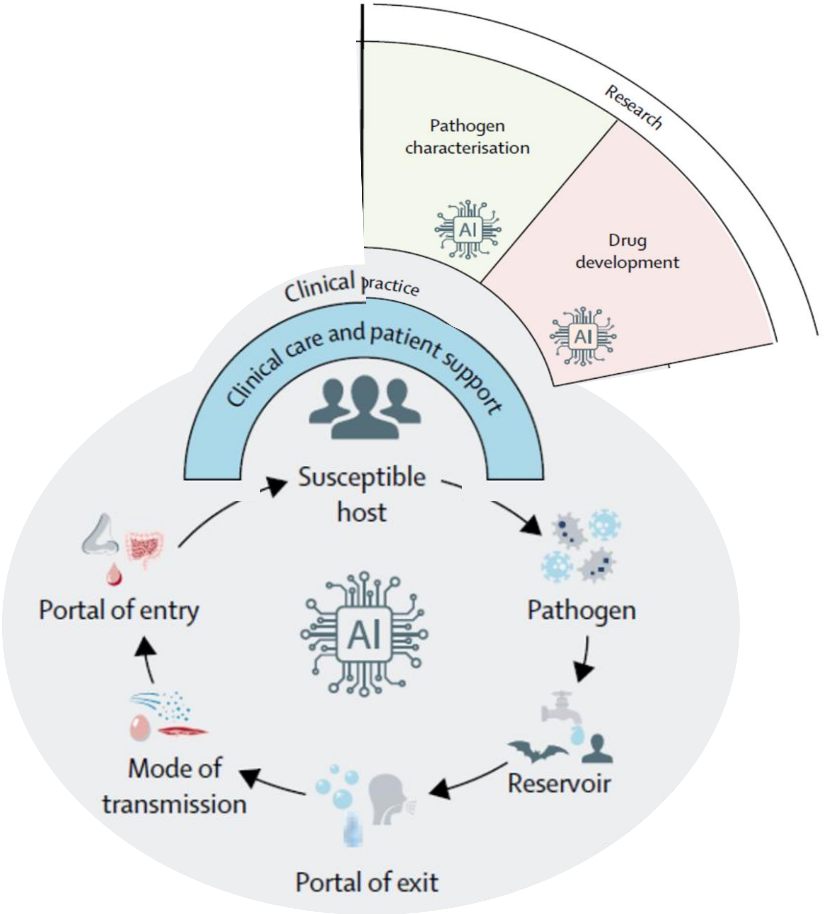
Second layer → Research
Domains:
- Pathogen characterization
- Drug Development

Pathogen characterisation

- Analysis of pathogen evolution and discovery of new microbial species
- Identification of virulence factors and assessment of host–pathogen interactions

Drug development

- Design and development of drugs and vaccines, including drug repurposing
- Identification and validation of therapeutic targets
- Development of innovative therapies



Public Health

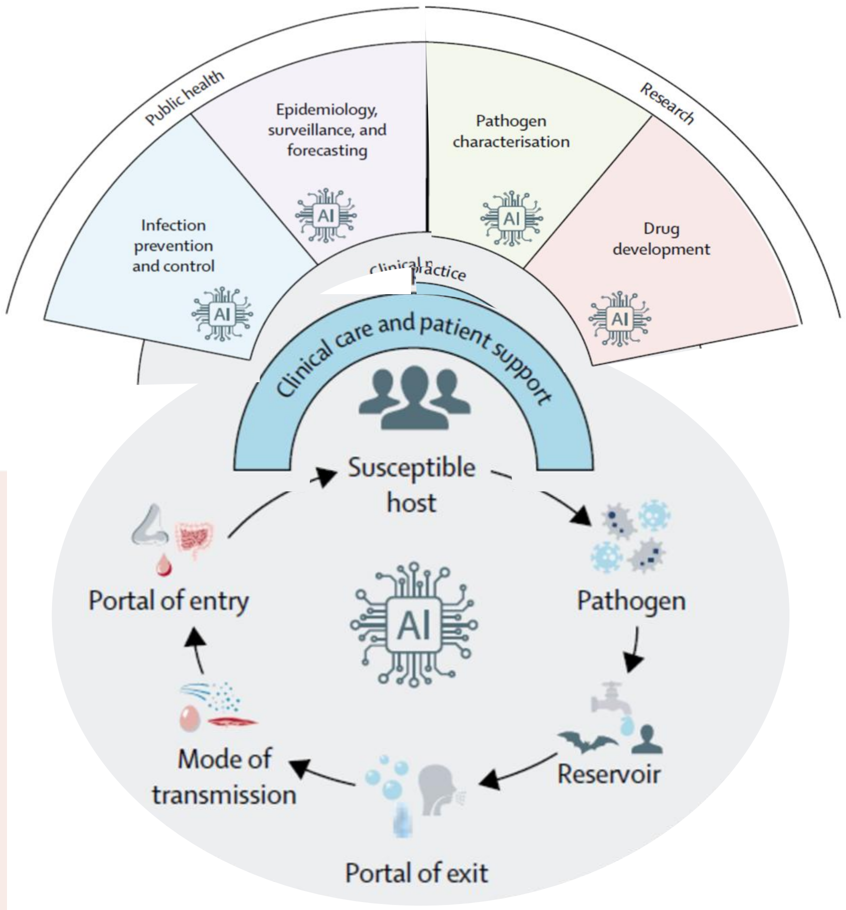
Third layer → Public Health
Domains:
- Epidemiology, surveillance and forecasting
- Infection prevention and control

» Epidemiology, surveillance, and forecasting

- Monitoring disease burden, trends, and infectious disease assessments
- Surveillance, genomic tracking, and environmental risk modelling
- Epidemic forecasting, scenario planning, decision support, and tackling misinformation

» Infection prevention and control

- Surveillance of health-care-associated infections and outbreak management
- Planning and evaluating prevention measures
- Training health-care providers and promoting population-level prevention



Focus – heath promotion

nature medicine

Article https://doi.org/10.1038/s41591-025-03618-6

A vaccine chatbot intervention for parents to improve HPV vaccination uptake among middle school girls: a cluster randomized trial

Received: 30 August 2024

Accepted: 26 February 2025

Published online: 7 April 2025

Check for updates

A list of authors and their affiliations appears at the end of the paper

Conversational artificial intelligence, in the form of chatbots powered by large language models, offers a new approach to facilitating human-like interactions, yet its efficacy in enhancing vaccination uptake remains under-investigated. This study assesses the effectiveness of a vaccine chatbot in improving human papillomavirus (HPV) vaccination among female middle school students aged 12–15 years across diverse socioeconomic settings in

Study aim

- Evaluate an **LLM-based chatbot** to **increase HPV vaccination uptake**
- Middle school girls (12-15 years), China
- **Out-of-pocket vaccination context**
- Explore mechanisms of AI-driven decision-making

Cluster randomised controlled trial (schools)
180 classes, 2,671 parents, stratified by socioeconomic context

- Intervention: **2-week chatbot (GPT-4, expert + nurse personas)**
- Control: **standard health promotion**

Outcomes
- Primary: **HPV vaccination uptake or booking**
- Secondary: **consultation, literacy, attitudes**

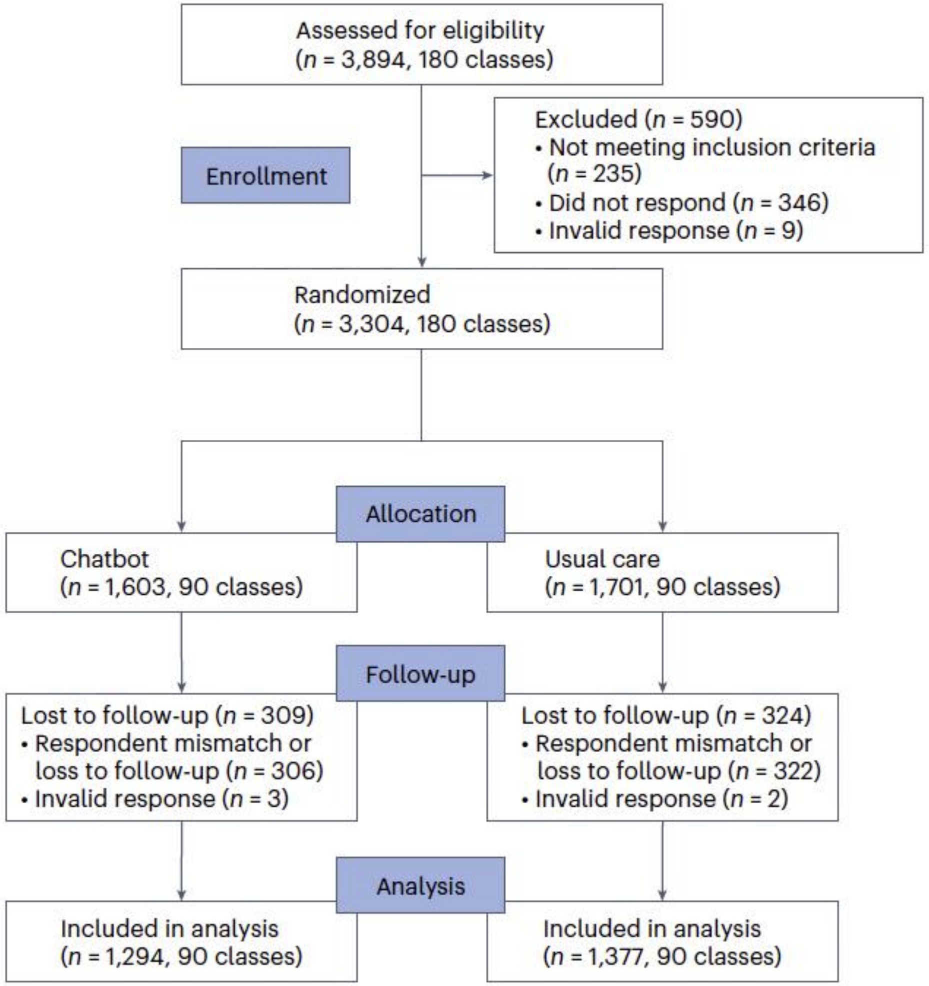


Fig. 1 | CONSORT flow diagram. The enrollment, randomization and follow-up of study participants from 180 classes across two study arms.

Focus – heath promotion

Table 3 | Effect of HPV vaccine chatbot intervention on primary and secondary outcomes

		Pre-intervention	Post-intervention	Post–pre difference (95% CI)	Adjusted RR (95% CI)	Coefficient (95% CI)	P value
HPV vaccine receipt or scheduled appointment among female students, n (%)	Chatbot	–	92 (7.1)	7.1 (5.7 to 8.5)	3.85 (2.48 to 5.97)		<0.001
	Usual care	–	25 (1.8)	1.8 (1.1 to 2.5)			
HPV vaccination-specific consultation, n (%)	Chatbot	–	635 (49.1)	49.1 (46.3 to 51.8)	2.73 (2.41 to 3.09)		<0.001
	Usual care	–	242 (17.6)	17.6 (15.6 to 19.7)			
Parental willingness to vaccinate their daughter, n (%)[a]	Chatbot	961 (74.3)	917 (70.9)	−3.4 (−6.8 to 0.0)	1.02 (0.98 to 1.07)		0.325
	Usual care	993 (72.1)	937 (68.1)	−4.1 (−7.5 to −0.7)			
High vaccine confidence, n (%)[b]	Chatbot	794 (61.4)	860 (66.5)	5.1 (1.4 to 8.8)	1.02 (0.97 to 1.08)		0.375
	Usual care	796 (57.8)	830 (60.3)	2.5 (−1.2 to 6.1)			
HPV-related literacy, mean (s.d.)	Chatbot	6.3 (3.1)	7.1 (2.8)	0.7 (0.5 to 1.0)		0.70 (0.52 to 0.88)	<0.001
	Usual care	6.1 (3.2)	6.2 (3.1)	<0.1 (−0.2 to 0.3)			
HPV-related literacy—knowledge, mean (s.d.)	Chatbot	3.9 (2.0)	4.3 (1.9)	0.5 (0.31 to 0.61)		0.38 (0.26 to 0.50)	<0.001
	Usual care	3.7 (2.0)	3.8 (2.0)	0.1 (−0.1 to 0.2)			
HPV-related literacy—rumor screening, mean (s.d.)	Chatbot	2.5 (1.5)	2.7 (1.4)	0.3 (0.2 to 0.4)		0.32 (0.21 to 0.43)	<0.001
	Usual care	2.4 (1.5)	2.4 (1.5)	<−0.1 (−0.2 to 0.1)			

	Number of participants			
	Chatbot n/N (%)	Usual care n/N (%)	Adjusted RR (95% CI)	P value
Overall participants	92/1,294 (7.1)	25/1,377 (1.8)	3.85 (2.48–5.97)	<0.001
Study region				
Megacity	26/480 (5.4)	7/487 (1.4)	3.84 (1.54–9.58)	0.004
Urban	41/432 (9.5)	15/462 (3.3)	2.80 (1.57–4.98)	<0.001
Rural	25/382 (6.5)	3/428 (0.7)	8.81 (2.74–28.35)	<0.001
Daughter left-behind				
Yes	3/67 (4.5)	0/70 (0.0)	–	–
No	89/1,227 (7.3)	25/1,307 (1.9)	3.73 (2.40–5.81)	<0.001
Parenthood				
Mother	83/1,139 (7.3)	22/1,203 (1.8)	3.99 (2.56–6.23)	<0.001
Father	9/155 (5.8)	3/174 (1.7)	2.86 (0.69–11.83)	0.147
Self or spouse HPV vaccinated				
Yes	28/294 (9.5)	10/340 (2.9)	3.12 (1.55–6.32)	0.002
No	64/1,000 (6.4)	15/1,037 (1.5)	3.90 (2.62–7.68)	<0.001
Education level				
High education	46/587 (7.8)	11/580 (1.9)	4.39 (2.41–8.01)	<0.001
Senior high school	15/226 (6.6)	7/256 (2.7)	2.13 (0.96–4.71)	0.063
Junior middle school and below	31/481 (6.4)	7/541 (1.3)	4.60 (1.95–10.87)	0.001
Employment				
Yes	27/410 (6.6)	8/416 (1.9)	3.55 (1.72–7.32)	0.001
No	65/884 (7.4)	17/961 (1.8)	4.12 (2.43–6.98)	<0.001
Household income				
>300,000 CNY	6/122 (4.9)	2/136 (1.5)	3.63 (0.70–18.74)	0.123
200,000–300,000 CNY	11/163 (6.8)	2/153 (1.3)	5.18 (1.05–25.61)	0.043
100,000–200,000 CNY	36/454 (7.9)	13/465 (2.8)	2.63 (1.52–4.56)	0.001
<100,000 CNY	39/555 (7.0)	8/623 (1.3)	5.31 (2.63–10.71)	<0.001

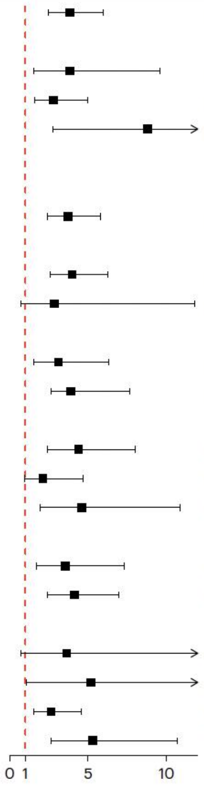


Fig. 2 | Stratified GEE to compare HPV vaccine receipt or scheduled appointment between two arms. Forest plot shows adjusted RR with two-sided 95% CI comparing HPV vaccine receipt or scheduled appointment between chatbot and usual care groups in each subgroup. The data present estimates from ITT analyses using stratified GEE models, with class as the cluster unit. The models adjusted for stratification variables and confounders including parents' characteristics (age, education level, employment, income, self or spouse HPV vaccination) and daughters' characteristics (age, only child, left-behind child, sexual education, influenza vaccination). No estimate was provided for the 'Daughter left-behind–Yes' subgroup owing to zero events in the usual care group. Statistical significance was set at $P < 0.05$ (two-tailed). CNY, Chinese Yuan.

- **Vaccination uptake**: 7.1% vs 1.8%
  → Adjusted RR 3.85 (p < 0.001)
- **Increased medical consultation** (49.1 vs 17.6)
- → Adjusted RR 2,73 (p < 0,001)
- **Improved health literacy**

Focus – heath promotion

Case studies: innovative solutions to sustain population level primary prevention and health promotion

nature human behaviour

Article https://doi.org/10.1038/s41562-024-01985-7

A behaviourally informed chatbot increases vaccination rates in Argentina more than a one-way reminder

Received: 26 November 2023

Accepted: 13 August 2024

Dan Brown[1], Adelaida Barrera[1], Lucas Ibañez[2], Iván Budassi[3], Bridie Murphy[1], Pujen Shrestha[1], Sebastian Salomon-Ballada[1], Jorge Kriscovich[4] & Fernando Torrente[5]

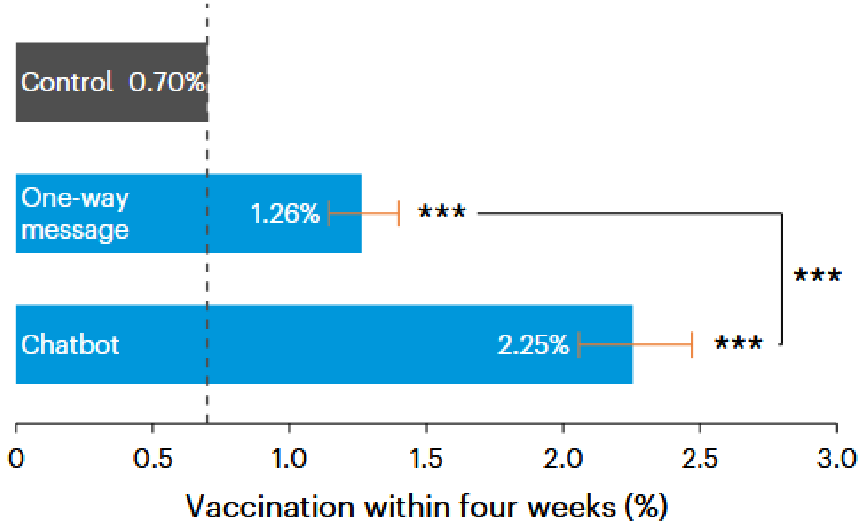


Fig. 2 | The effect of the behaviourally informed chatbot on uptake of the next dose of the COVID-19 vaccine, compared with a one-way message and the control group. Comparison of the vaccination rate in the control group

Focus – heath prevention and IPC in hospitals

monitoring compliance with infection control measures

Neural Computing and Applications (2023) 35:15981–15996
https://doi.org/10.1007/s00521-022-07194-5

S.I.: AI-BASED E-DIAGNOSIS

A deep learning based system for handwashing procedure evaluation

Antonio Greco[1] · Gennaro Percannella[1] · Pierluigi Ritrovato[1] · Alessia Saggese[1] · Mario Vento[1]

Received: 5 October 2021 / Accepted: 10 March 2022 / Published online: 21 April 2022

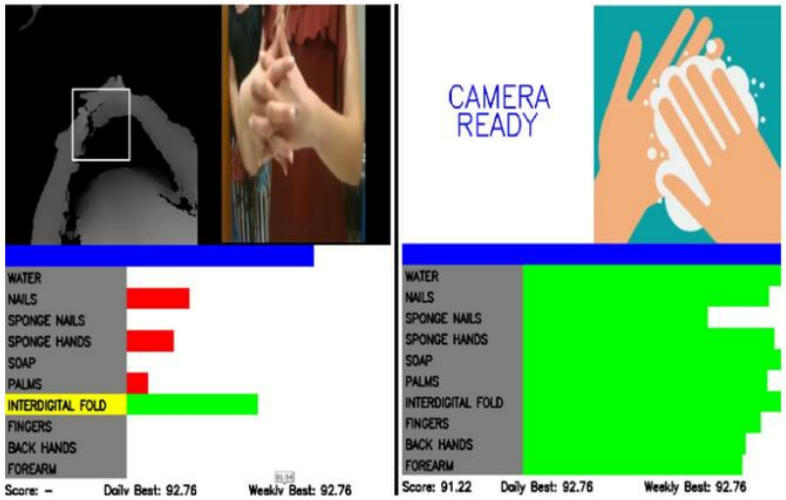


Fig. 3 Handwashing system GUI: Real-time feedback (Left); Overall performance (right)

OPEN ACCESS Freely available online PLOS ONE

Efficacy of a New Educational Tool to Improve Handrubbing Technique amongst Healthcare Workers: A Controlled, Before-After Study

Andrew J. Stewardson[1]*, Anne Iten[1], Véronique Camus[1], Angèle Gayet-Ageron[1,2], Darren Caulfield[3], Gerard Lacey[3,4], Didier Pittet[1]

1 Infection Control Program and World Health Organization Collaborating Centre on Patient Safety, University of Geneva Hospitals and Faculty of Medicine, Geneva, Switzerland, **2** Division of Clinical Epidemiology, University of Geneva Hospitals and Faculty of Medicine, Geneva, Switzerland, **3** Glanta Ltd, Dublin, Ireland, **4** School of Computer Science and Statistics, Trinity College Dublin, Dublin, Ireland

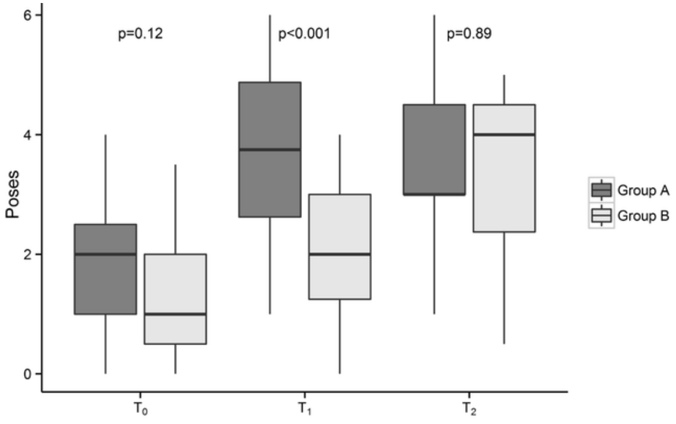


Figure 4. Number of poses performed correctly per hand hygiene action, by study group and study phase. Group A was exposed t

The number of poses performed correctly per hand hygiene action significantly increased between baseline (T0) and Follow-up 1 and 2 (T1, T2)

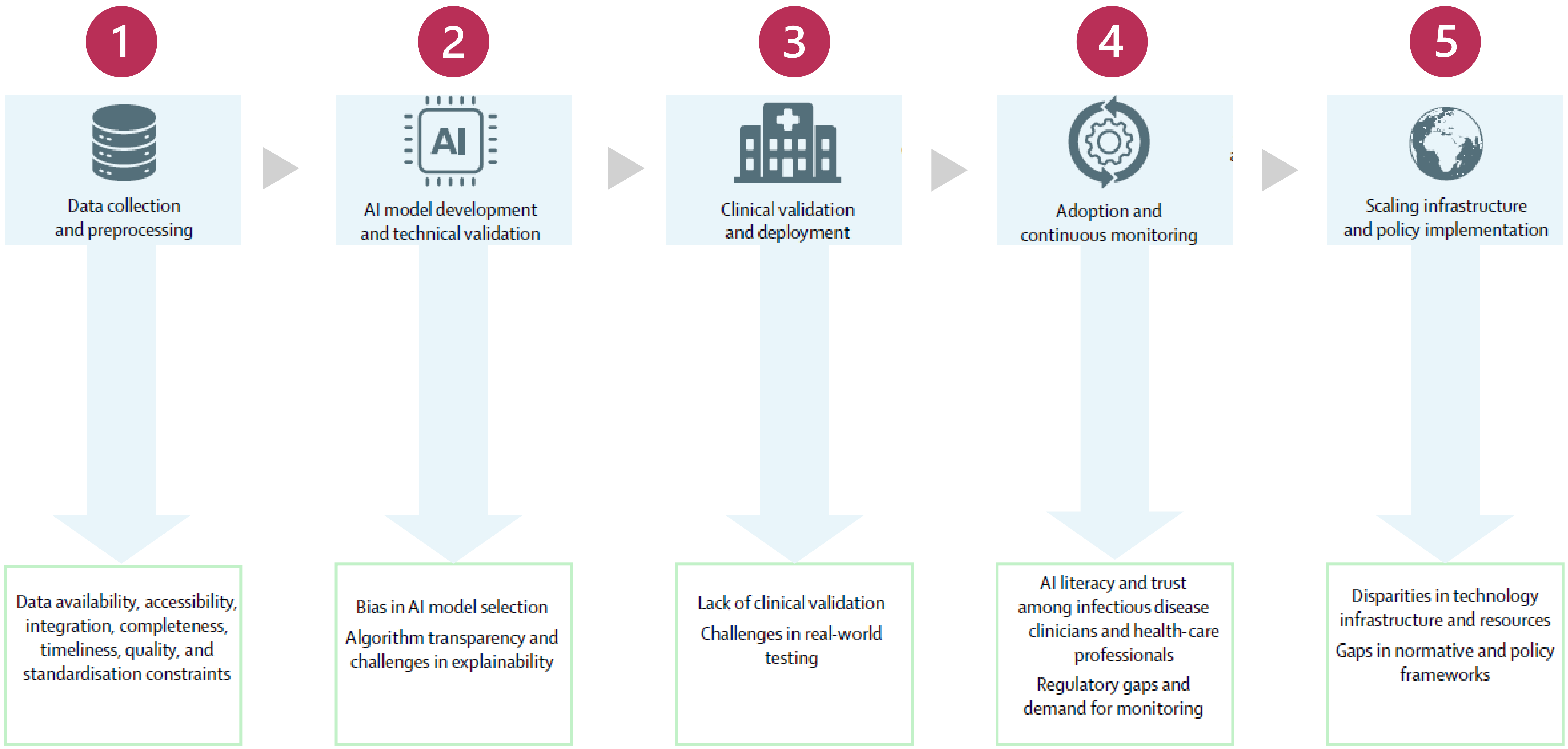
The potential value

	Potential AI-supported applications	Potential care advantages	Potential societal goals	Layer-specific barriers
Clinical practice layer				
Clinical care and patient support	Clinical reasoning support—risk factors identification, clinical signs, and symptom assessment; diagnostic pathway—imaging, laboratory and microbiological investigations support (pathogen and antibiotic resistance genes detection, and AMR prediction); risk stratification and prognostic evaluation; therapeutic intervention support: antimicrobial prescription and treatment optimisation; antimicrobial stewardship implementation and monitoring; patient follow-up and outcomes assessment; patient engagement and symptoms tracking; treatment compliance support; adaptive patient communication; patient health education and promotion	Increased speed and automation of clinical workflow; increased diagnostic accuracy; increased treatment efficacy and appropriateness; precision medicine and personalised therapeutics approaches; improved patient outcomes; optimised human and organisational resources use; increased patient-centred care	Health equity; health systems and services sustainability; patient and community empowerment; life-science innovation, research, and development; strengthened public health preparedness	Data heterogeneity and fragmentation across EHR systems; bias in model development and training; absence of prospective clinical validation and RCTs; integration challenges into clinical workflows; low AI literacy and trust among infectious disease clinicians; privacy and data protection concerns; low explainability and transparency in clinical decision making; emerging risks from LLM-based chatbots (eg, misinformation, hallucinations, and over-reliance)
Public health layer				
Infection prevention and control	HAI surveillance; outbreak management; IPC intervention planning, implementation, and monitoring; HCP education and training; population-level primary prevention and health promotion	Increased personalisation and timely response; improved patient safety; increased training and compliance monitoring	Health equity; health systems and services sustainability; patient and community empowerment; life-science innovation, research, and development; strengthened public health preparedness	Incomplete and siloed surveillance and population-level data; absence of data standardisation and interoperability; low prospective field validation; skills and training gaps among public health professionals; infrastructural disparities across countries; fragmented regulatory and governance frameworks
Epidemiology, surveillance, and forecasting	Disease burden and epidemiological trends monitoring; infectious disease epidemiology assessment; epidemic forecasting and nowcasting (early warning, hotspot detection and outbreak forecasting); passive and active human surveillance; genomic surveillance and variant tracking; scenario modelling and public health decision support; public perception and misinformation monitoring; integrated surveillance, zoonotic, and environmental risk modelling	Increased timeliness, completeness, and representativeness of surveillance systems; increased real-time monitoring; integration of diverse and complex data sources in human, animal, and environmental health; improved public health adaptive response	Health equity; health systems and services sustainability; patient and community empowerment; life-science innovation, research, and development; strengthened public health preparedness	Incomplete and siloed surveillance and population-level data; absence of data standardisation and interoperability; low prospective field validation; skills and training gaps among public health professionals; infrastructural disparities across countries; fragmented regulatory and governance frameworks
Research layer				
Pathogen characterisation	Pathogen evolution analysis; new microbial species discovery; virulence factor identification; host–pathogen interaction assessment	Improved response to pathogen evolution; increased understanding of pathogen behaviour	Health equity; health systems and services sustainability; patient and community empowerment; life-science innovation, research, and development; strengthened public health preparedness	Absence of standardised, high-quality annotated datasets; barriers to data sharing and reuse; little experimental validation of AI-generated research outputs; challenges in translating AI discoveries into regulated pipelines; gaps in ethical, legal, and regulatory frameworks for AI-driven research
Drug development	Drug and vaccine design and development; drug repurposing; therapeutics target identification and validation; innovative therapy development	Drug and vaccine development acceleration; improved therapeutic precision; optimised cost, time and resource use	Health equity; health systems and services sustainability; patient and community empowerment; life-science innovation, research, and development; strengthened public health preparedness	Absence of standardised, high-quality annotated datasets; barriers to data sharing and reuse; little experimental validation of AI-generated research outputs; challenges in translating AI discoveries into regulated pipelines; gaps in ethical, legal, and regulatory frameworks for AI-driven research

AMR=antimicrobial resistance. EHRs=electronic health records. HAI=health-care-associated infections. HCPs=health-care providers. IPC=infection prevention and control. LLMs=large language models. RCTs=randomised controlled trials.

Table 2: Conceptual framework for artificial intelligence applications in infectious disease prevention and management: layers, domains, potential applications, advantages, and barriers

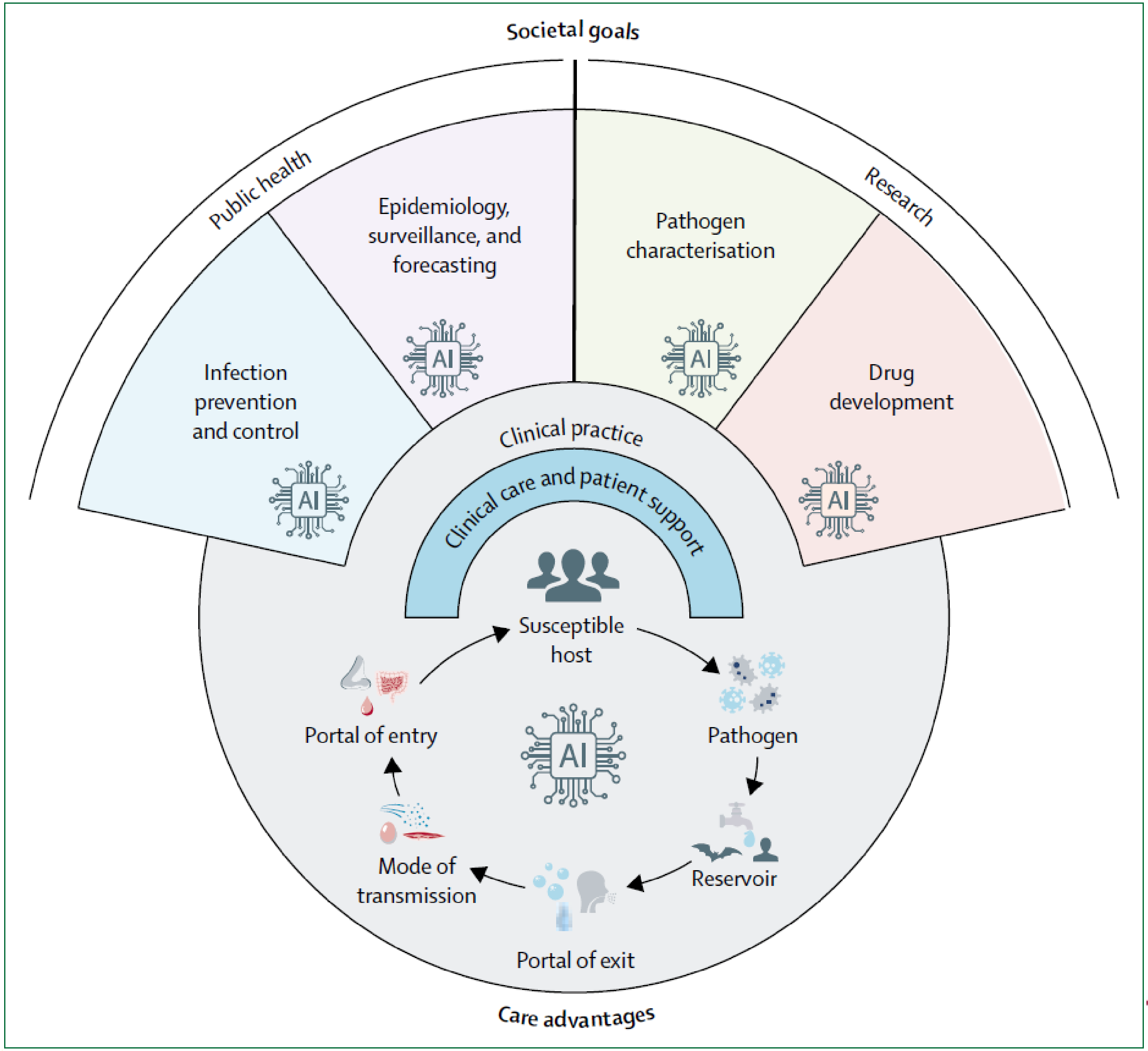
Barriers to AI potential exploitation



Conclusions/1

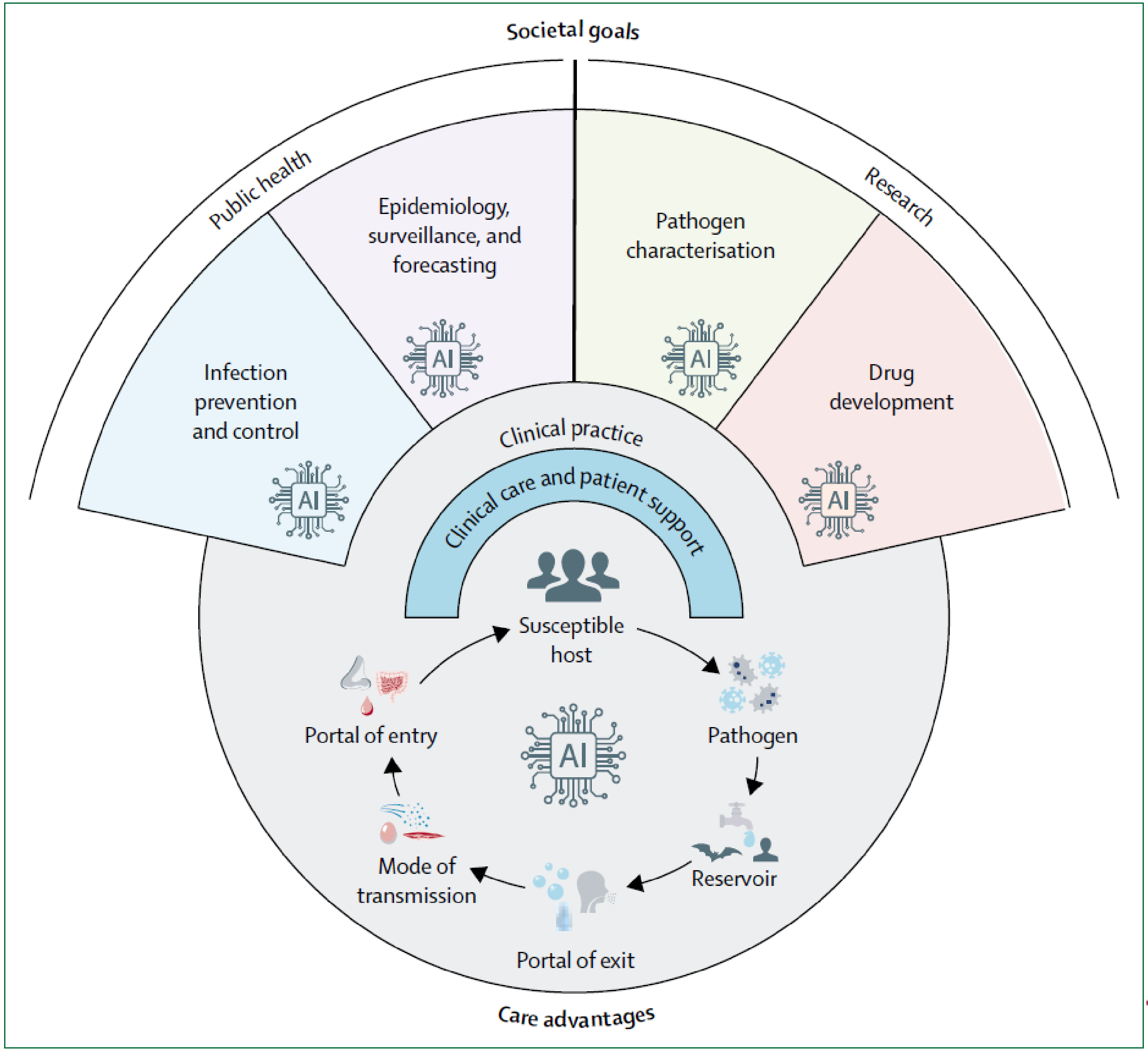
- Through the proposed framework, we have outlined how AI has the potential to revolutionise infectious disease prevention and management in the years to come by supporting clinical practice, public health, and research.

- The level of AI maturity is still scarce and varies across different domains.



Conclusions/2

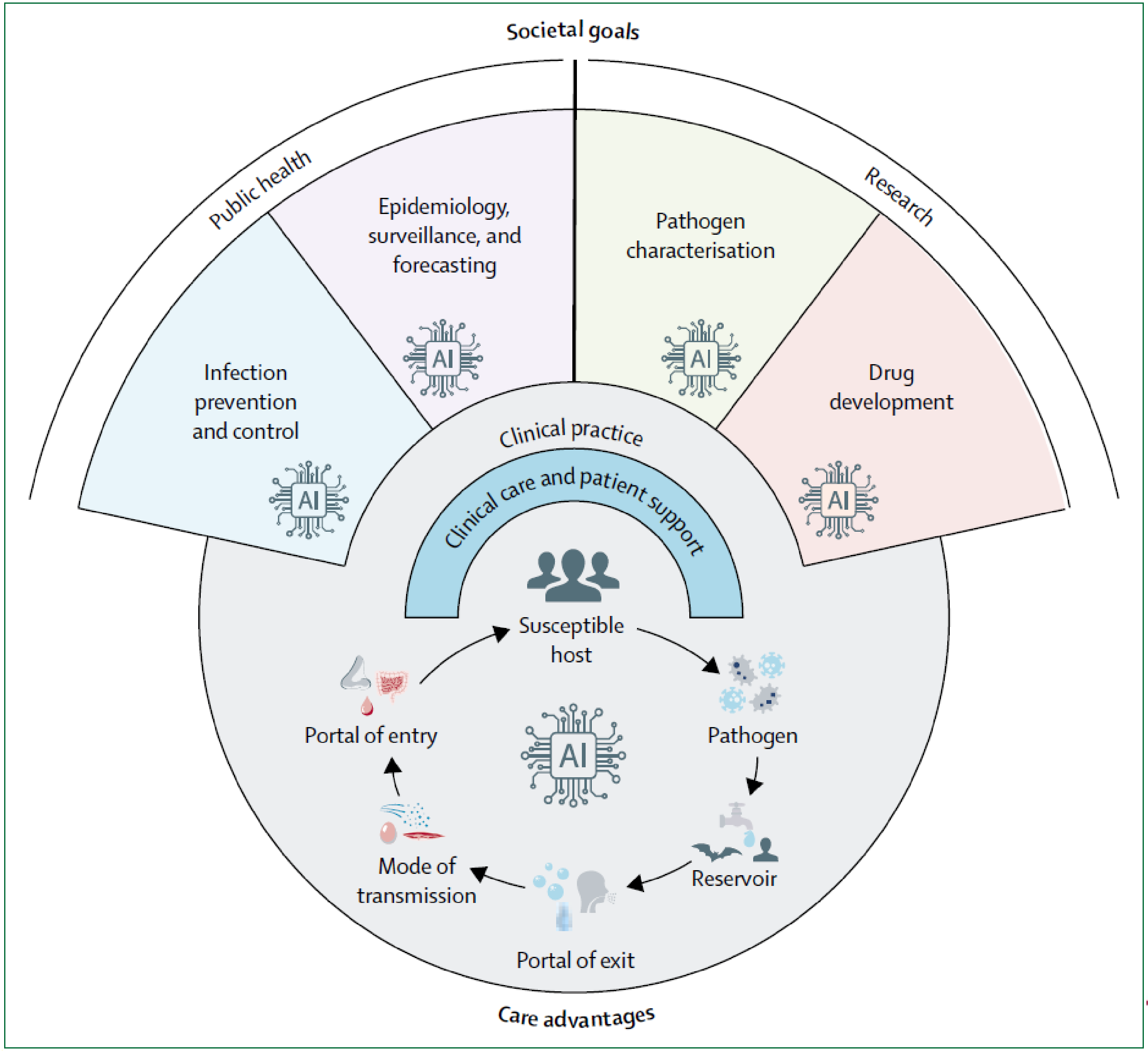
- Many barriers limit the translation of AI's potential into practice, including:
  - availability and quality of data
  - gaps in clinical validation
  - regulatory and ethical barriers
  - scepticism and lack of training among infectious disease professionals.
- Active engagement of infectious disease professionals is essential to guide the planning, implementation, and monitoring of AI applications.



UNIVERSITÀ DI PAVIA

Conclusions/3

Although there is no doubt that AI will continue to evolve, the direction it will take and the health value it will convey in the future depend on how we, as professionals, choose to get involved today.



UNIVERSITÀ DI PAVIA

31st International Conference on Health Promoting Hospitals and Health Services

Conference program

May 20-22, 2026
Slagthuset, Malmö, Sweden

www.hphconferences.org/nc/malmo2026

International Network of
Health Promoting Hospitals
& Health Services

Thank you!

anna.odone@unipv.it

UNIVERSITÀ
DI PAVIA

BOX 2 - Pillars for a successful European strategy for public health digitalization

1. **Political commitment:** strong political commitment and Government leadership are needed to implement digital public health strategies at the national level and across Europe
2. **Normative and regulatory frameworks:** a clear set of regulation should support interoperability to allow safe and effective data exchange between different information and communication technology systems at the national and European level
3. **Technical infrastructure:** National and regional health authorities, as well as hospitals and healthcare agencies should be equipped with technical infrastructure to support the implementation of digital solutions
4. **Economic investments:** the successful implementation of digital public health solutions need targeted public and private economic investments
5. **Training and education**: the public health workforce need to be trained to embrace digital solutions and university curricula should increasingly include multidisciplinary digital health modules
6. **Research**: R&D as well as operational research should be carried out drawing from health services and biomedical informatics scholarly for studies of digital health interventions
7. **Monitoring and evaluation:** the introduction and monitoring of public health digital solutions in different settings should be supported by technology evaluations based on targeted, solid and shared HTA models