LISBON ECONOMICS

Artificial Intelligence in Medicine

A comparative review of leading academic medical centers in the United States and Europe

Working Paper 1/2026

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[1] We thank to all team of Lisbon Economics the comments and ideas in the numerous sessions of discussion. We also thank Professor Margarida Mateus for her cooperation.

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ABSTRACT

Artificial intelligence (AI) has moved from algorithmic novelty to a routine component of clinical workflow, biomedical discovery, and medical education. Drawing on a comparative review of six leading United States academic medical centers (UCSF, Stanford, MIT, Harvard/Mass General Brigham, NYU Langone, Duke) and four European peers (Oxford, ETH Zurich, Karolinska Institute, KU Leuven), this paper assesses (i) how far AI has progressed in supporting medical practice and teaching, (ii) why the United States currently leads Europe in clinical AI translation, and (iii) what role European universities can play in closing the gap. We document deployed systems including the NYUTron clinical language model (4.1B-word corpus, 387,144 patients) and Duke Sepsis Watch (27% sepsis mortality reduction since 2018), survey 2025 trends in npj Digital Medicine, and benchmark institutions across mission, infrastructure, governance, and education. We argue the US lead is structural — vertically integrated academic medical centers, philanthropic capital concentration, federated health-system data, and a permissive early-stage innovation regime — rather than scientific. Europe retains decisive advantages in regulatory maturity (EU AI Act), cross-border data infrastructure (European Health Data Space), and population-scale clinical validation. We conclude with a six-point agenda for European universities to convert these advantages into translational leadership.

KEYWORDS

Clinical artificial intelligence; medical education; foundation models; clinical decision support; EU AI Act; European Health Data Space; comparative health policy; academic medical centers.

CHAPTER 1 · INTRODUCTION

The integration of artificial intelligence into medicine has shifted from speculative promise to operational reality. Foundation models read electronic health records in real time; deep learning systems flag deteriorating patients hours before clinical presentation; generative models propose candidate antibiotics from molecular libraries. Within five years, the central question for academic medicine has moved from 'can AI work in medicine?' to 'who will scale it, govern it, and teach it?' ·

This paper examines that transition through three lenses. First, we survey the maturation of clinical AI in the United States, where flagship deployments at NYU Langone, Duke, MIT, Stanford, and UCSF have produced both peer-reviewed evidence and routine clinical use. Second, we analyze the European landscape, where world-class research institutions, the most advanced regulatory framework for medical AI globally (the EU AI Act), and the federated data infrastructure of the European Health Data Space (EHDS) coexist with comparatively slower translational throughput. Third, we synthesize the structural reasons for the US lead and propose a strategic agenda for European universities.

Our argument is not that the United States produces better science, but that the American academic medical center is a more efficient translation engine, and that this efficiency is now the binding constraint on European competitiveness in clinical AI.

CHAPTER 2 · MATERIALS AND METHODS

We employed a structured comparative review across two cohorts of academic medical centers selected for their visibility in the AI-in-medicine literature and their distinct institutional models:

- United States cohort (n=6): UCSF Bakar Computational Health Sciences Institute (BCHSI); Stanford Center for AI in Medicine and Imaging (AIMI) and the affiliated RAISE Health initiative; MIT Abdul Latif Jameel Clinic for Machine Learning in Health; Harvard Medical School / Mass General Brigham AI ecosystem; NYU Grossman School of Medicine and NYU Langone Health; Duke Institute for Health Innovation (DIHI).
- European cohort (n=4): University of Oxford; ETH Zurich; Karolinska Institute; KU Leuven.

For each institution we extracted (i) mission and strategic focus, (ii) flagship research outputs, (iii) data infrastructure, (iv) education and workforce programs, (v) industry and clinical partnerships, and (vi) governance posture. Sources include institutional reports, peer-reviewed publications (with particular emphasis on the 2025 corpus of npj Digital Medicine), the WHO European Region 2024–2025 assessment of AI integration across 50 countries, the Joint Research Centre (JRC) of the European Commission, and the Horizon Europe RAISE programme documentation.

Limitations: The cohorts are not exhaustive and selection favors high-visibility centers; institutional self-reporting may overstate deployment maturity; and direct quantitative comparison of clinical impact across health systems is constrained by heterogeneous outcome reporting. We mitigate this by anchoring claims to peer-reviewed performance metrics where available (e.g., NYUTron AUC ranges, Sepsis Watch external validation in npj Digital Medicine, 2025) and by triangulating across independent sources.

CHAPTER 3 · THE MATURATION OF AI IN MEDICAL PRACTICE

Five exemplar deployments illustrate the present frontier of clinical AI. Each addresses a distinct translational bottleneck — direct EHR integration, real-time decision support, drug discovery, population-scale analytics, and imaging — and each is operating in routine clinical or scientific use rather than in pilot.

3.1 Clinical Language Models at Health-System Scale: NYUTron

NYUTron, developed by NYU Grossman School of Medicine and deployed across NYU Langone Health, is a large clinical language model trained on 4.1 billion words of inpatient notes spanning ten years of EHR data and 387,144 patients. Its design solves the 'last-mile problem' of clinical AI: most predictive models never reach deployment because they require structured data and bespoke preprocessing. NYUTron instead reads physicians' free-text documentation directly.

Across five evaluation tasks — 30-day readmission, in-hospital mortality, comorbidity index, length-of-stay, and insurance-denial prediction — NYUTron achieved AUCs of 78.7–94.9%, with 5.36–14.7% absolute improvement over standard models. It correctly identifies 80% of readmissions, predicts 85% of in-hospital deaths, and accurately estimates 79% of length-of-stay outcomes. The system is in active clinical use, alerting clinicians to high-risk patients in real time.

3.2 Real-Time Decision Support: Duke Sepsis Watch

Sepsis Watch is among the first deep-learning early-warning systems fully integrated into routine US clinical care, operating continuously across the Duke University Health System since November 2018. The model was trained on more than 42,000 patient encounters and 32 million data points, ingesting 86 real-time variables sampled every five minutes.

Outcomes attributed to Sepsis Watch include doubling of three-hour SEP-1 bundle compliance, a 27% reduction in sepsis-related mortality at Duke University Hospital, and prediction of sepsis a median of five hours before clinical presentation. External validation across four Summa Health emergency departments (Ohio), reported in npj Digital Medicine in 2025, found AUROC of 0.906–0.960, demonstrating robust portability with minimal local adaptation. The case is widely cited as evidence that workflow-aware design — including a dedicated rapid-response nursing team that mediates alerts — is a more decisive factor in clinical impact than raw model performance.

3.3 AI-Enabled Discovery: MIT Jameel Clinic

Founded in 2018 as a joint initiative between MIT and Community Jameel, the Jameel Clinic has become the most visible academic center for AI-driven drug discovery. Its breakthroughs include the deep-learning identification of two novel antibiotics (Halicin and Abaucin) from molecular screens, the MIRAI breast cancer prediction model from mammography, and the SYBIL deep-learning system for lung cancer risk prediction from low-dose CT. The Clinic supports a global network of 65–110 hospitals with free access to its tools, an explicit equity strategy that distinguishes it from purely commercial AI vendors.

3.4 Population-Scale Computational Health: UCSF BCHSI

The UCSF Bakar Computational Health Sciences Institute operates at the intersection of biomedical informatics, multi-omics, and population health. Its access to the University of California Health System data warehouse — covering approximately 40 million patients across UC's clinical sites — supports work spanning AI-driven preterm birth prediction (Cell), cell-specific approaches to Alzheimer's disease, and large-scale analyses of mental health and cancer outcomes. BCHSI is also the institutional home of NLP@UCSF, a community advancing natural language processing on clinical text, and of bioinformatics PhD and clinical informatics fellowship programs that have become a national pipeline for clinician-data scientists.

3.5 Imaging AI and the Open-Science Model: Stanford AIMI / RAISE Health

Stanford's AIMI Center, founded in 2018, anchors what is arguably the largest academic ecosystem for imaging AI globally. AIMI's release of more than twenty AI-ready clinical datasets, including the CheXpert chest radiograph corpus, has shaped the field's evaluation norms. RAISE Health, a joint initiative with Stanford HAI under co-directors Fei-Fei Li and James Landay, complements AIMI's technical mission with a governance and ethics mandate, an institutional pattern (technical center + paired governance institute) that has become an emerging norm for serious health-AI programs.

3.6 The 2025 Research Frontier

Five themes dominate the 2025 corpus of npj Digital Medicine and adjacent venues:

1. Clinically validated AI models, with a heavy oncology and imaging skew (3D deep-learning quantification of vascular invasion in pancreatic cancer; multimodal survival prediction in colorectal cancer; deep learning for maxillary sinus segmentation).
2. Foundation and reasoning models entering clinical evaluation, including large reasoning models in radiology and foundation-model–guided semi-supervised CT segmentation.
3. Multimodal and multi-omics fusion, integrating imaging, clinical, and genomic data toward holistic patient modeling.
4. Digital health and remote monitoring, including telemonitoring after cancer surgery and digital interventions for mental health in oncology.
5. Fairness, governance, and data protection, with a marked rise in scoping reviews of clinical AI fairness and frameworks for preventing unmonitored AI experimentation.

CHAPTER 4 · AI IN MEDICAL EDUCATION AND WORKFORCE DEVELOPMENT

Education has lagged clinical deployment but is converging quickly. Across the US cohort, four education models have emerged: (i) longitudinal clinician-scientist tracks (UCSF bioinformatics PhD and clinical informatics fellowships), (ii) executive and leadership education (Stanford AIMI's Leadership and Strategy Course in Healthcare AI), (iii) intensive bootcamps and pre-graduate outreach (MIT Jameel AI & Health Bootcamps; Stanford high-school AI programs), and (iv) regulatory-science curricula (Harvard/MGB FDA-aligned training).

European programmes — including KU Leuven's hospital-embedded clinical AI training, Karolinska's clinical informatics offerings, and ETH Zurich's biomedical engineering tracks — match the US in depth but not in scale or in integration with deployed clinical systems. The gap is most visible in the absence, across most European medical schools, of mandatory AI literacy in the core MD curriculum: students still graduate without structured exposure to model interpretation, algorithmic bias, or human–AI clinical decision-making.

CHAPTER 5 · THE US ECOSYSTEM: A STRUCTURAL ANATOMY

Table 1 benchmarks four leading US institutions across the dimensions that shape translational throughput. The pattern is one of complementary specialization within a tightly integrated ecosystem rather than uniform excellence.

Table 1 Benchmarking of leading US academic AI-in-medicine centers

Dimension	MIT Jameel Clinic	Stanford AIMI	UCSF BCHSI	Harvard / MGB

Strategic focus	AI drug discovery + clinical AI + global deployment	Imaging AI + multimodal models + open science	Computational health, precision medicine, multi-omics	Clinical AI + regulatory science across MGB
Flagship outputs	Halicin & Abaucin antibiotics; MIRAI; SYBIL	CheXpert; multimodal foundation models; 20+ open datasets	Preterm birth prediction (Cell); Alzheimer's cell-type models	FDA-cleared imaging tools; MGH/BWH AI evaluation frameworks
Data assets	Molecular libraries; 65–110 hospital network	Large imaging repositories; AIMI Data Commons	UC-wide ~40M patient warehouse	Largest US hospital-based imaging archive
Education model	Bootcamps; AI Cures; global outreach	Leadership courses; high-school AI programs	Bioinformatics PhD; clinical informatics fellowships	FDA-oriented regulatory science training
Industry partners	Takeda, Sanofi, Wellcome Trust	Big tech, imaging vendors, cloud	NIH, UC Health, biotech	MGB Innovation, FDA, pharma
Governance	Equity-of-access focus	RAISE Health (dedicated responsible-AI institute)	Clinical data governance and equity	FDA-aligned evaluation; clinical-trial governance

Five structural features explain the throughput of this ecosystem:

6. Vertically integrated academic medical centers. NYU Grossman and NYU Langone are administratively coupled; the same is true of UCSF and UCSF Health, of Duke and the Duke University Health System, and of Harvard Medical School and Mass General Brigham. A model developed in the medical school can be deployed in the affiliated hospital under unified governance — a configuration rare in Europe, where universities and teaching hospitals are typically separately governed.
7. Philanthropic capital concentration. The Bakar, Jameel, and Chan Zuckerberg endowments, alongside the forthcoming Bakar Research and Academic Building (UCSF, opening 2028), supply patient capital on a scale European universities cannot match from public funding alone.
8. Federated data at health-system scale. Mass General Brigham operates the largest hospital-based imaging archive in the United States; UC Health gives BCHSI access to roughly 40 million patient records; NYU Langone supplied the 4.1-billion-word corpus underlying NYUTron. Comparable European assets exist (UK Biobank, Karolinska clinical registries) but are typically governed for research rather than for embedded clinical deployment.
9. Permissive early-stage innovation regime. The US FDA has cleared a steadily growing roster of AI/ML medical devices, while leaving substantial room for non-device clinical decision support to deploy under institutional governance. The EU AI Act, by contrast, classifies most medical AI as high-risk from inception, raising the floor for compliance — a feature in the long run, but a friction in the short run.
10. Open dataset and convening culture. Stanford AIMI's twenty-plus public datasets, the Jameel Clinic's AI Cures convenings, and the AIMI Symposium have created network effects that draw talent and partnerships into the US ecosystem.

CHAPTER 6 · THE EUROPEAN LANDSCAPE

European leadership in clinical AI is real but differently configured. Excellence is distributed across institutions rather than concentrated in a handful of academic medical centers, and the binding constraints are governance and infrastructure rather than scientific capacity.

6.1 Institutional Strengths

Table 2 benchmarks four leading European centers. ETH Zurich anchors technical depth; Karolinska Institutet leads in clinical translation and population-scale validation; Oxford fuses biomedical AI with NHS-scale clinical trials; KU Leuven is among Europe's strongest centers for imaging AI and hospital-embedded research.

Table 2 Benchmarking of leading European academic AI-in-medicine centers

Dimension	Oxford	ETH Zurich	Karolinska Institutet	KU Leuven
AI-in-medicine breadth	Very broad: imaging, oncology, cardiology, genomics	Extremely broad: multimodal AI, robotics, privacy-preserving AI	Broad: oncology, cardiology, emergency care, mental health	Broad: imaging, computational biology, clinical AI
Clinical integration	Strong via NHS partnerships	Moderate; strong engineering–hospital collaborations	Very strong; national-scale deployments	Very strong; University Hospitals Leuven
Flagship achievements	AI for cancer detection; AI–genomics; NHS-scale trials	Multimodal medical AI; explainable AI; generative biomedical models	Breast cancer AI; emergency triage; tumor analysis	Radiology, cardiology, and surgical AI
Regulatory alignment	Strong (UK MHRA + EU collaborations)	Strong (EU AI Act compliance research)	Very strong (clinical validation pipelines)	Very strong (EU AI Act + clinical trials)
Data infrastructure	NHS datasets + Oxford Big Data Institute	ETH biomedical data hub	Karolinska clinical registries	KU Leuven hospital data ecosystem
Population-level AI	Strong (UK Biobank)	Moderate	Very strong	Strong

6.2System-Level Integration

The 2024–2025 WHO European Region assessment is the first region-wide evaluation worldwide of AI readiness and deployment across fifty countries. It documents national-scale integration of AI in clinical decision support, predictive analytics, triage, and population-level health management. No other world region has implemented AI in healthcare at this scale with coordinated governance, making Europe a global reference model for system-level integration even where individual institutional outputs lag US peers.

6.3 Regulatory Leadership: The EU AI Act

The EU AI Act classifies most medical AI systems as high-risk and requires rigorous clinical validation, transparency, human oversight, post-market monitoring, and bias mitigation. The regulation imposes near-term friction on rapid deployment but produces a stable, trusted environment for clinical adoption — a long-term competitive advantage that is already shaping global standards for medical AI.

6.4The European Health Data Space

The European Health Data Space (EHDS) is creating one of the world's largest federated health-data infrastructures, enabling cross-border research, AI-driven discovery, and secure access to clinical, genomic, and imaging datasets at multi-institution scale. For universities, the EHDS is the structural answer to the US health-system data advantage: it converts the European preference for interoperability and patient sovereignty into a research asset that, in principle, exceeds any single US health-system warehouse.

6.5 RAISE: Europe's Horizon Europe AI-in-Science Institute

The Resource for AI Science in Europe (RAISE), launched by the European Commission, is a €107M Horizon Europe initiative establishing a virtual institute for frontier AI research, with explicit applications to cancer treatment optimization, environmental and epidemiological modeling, and large-scale scientific data integration. RAISE is part of a broader strategy to double EU AI research funding to over €3B annually and is the first transnational AI-science institute pooling compute, data, and talent across all member states.

CHAPTER 7 · WHY THE UNITED STATES LEADS: A COMPARATIVE DIAGNOSIS

The US lead in clinical AI translation is structural rather than scientific. Five factors, summarized in Table 3, account for most of the gap.

Table 3 Structural factors behind the US lead in clinical AI translation

Factor	United States	Europe	Net effect
Academic medical center integration	Universities and teaching hospitals share governance (UCSF/UCSF Health; NYU/NYU Langone; Harvard/MGB)	Universities and hospitals typically separately governed; deployment requires multi-party agreements	Faster US bench-to-bedside loop
Capital structure	Concentrated philanthropy (Bakar, Jameel, Chan Zuckerberg); large endowments	Predominantly public funding; smaller per-institution capital	US can sustain multi-year translational programs at scale
Health-system data access	Federated within single health system (NYU 4.1B-word corpus; UC Health 40M patients)	Higher-quality but fragmented; EHDS still maturing	US currently faster for proprietary deployment; Europe faster long-term for cross-border research
Regulatory regime	FDA device pathway + permissive non-device clinical decision support	EU AI Act classifies most medical AI as high-risk from inception	Short-term US speed advantage; long-term EU credibility advantage

Open science and convenings	20+ Stanford AIMI datasets; AI Cures; AIMI Symposium	Strong national programs (e.g., Karolinska) but fewer continental convenings	US benefits from network effects and talent pull

Two qualifications matter. First, the US lead is in deployment throughput, not in research originality — Europe contributes a comparable share of high-impact publications and disproportionately leads on fairness, governance, and explainability research. Second, the US model carries risks the European model is engineered to avoid: commercial pressure on deployment timelines, weaker post-market surveillance, and equity gaps when reimbursement rather than population coverage drives adoption. Europe's regulatory and population-health orientation is a feature, not a bug.

CHAPTER 8 · THE STRATEGIC ROLE OF EUROPEAN UNIVERSITIES

European universities are uniquely positioned to convert the continent's regulatory and infrastructure advantages into translational leadership. Six priorities emerge from this analysis.

8.1 Establish multidisciplinary AI-in-medicine centers

European universities should follow the AIMI / RAISE Health dual-pillar model: a technical center for model development paired with a governance institute for ethics, safety, and policy. The configuration matches both EU AI Act requirements and the structural pattern of leading US peers.

8.2 Mandatory AI literacy in the medical curriculum

Every medical graduate should have structured exposure to model interpretation, algorithmic bias, human–AI clinical decision-making, data governance, and the fundamentals of digital diagnostics and precision medicine. This is the single highest-leverage curricular reform available and should be implemented at the bachelor and master MD level rather than deferred to specialty training.

8.3 Build EU AI Act–aligned clinical validation pipelines

Compliance is a competitive advantage when it is designed in rather than retrofitted. Universities that operationalize Act-aligned validation pipelines — covering clinical evaluation, post-market monitoring, bias auditing, and human oversight — will be the partners of choice for industry and for cross-border deployment.

8.4 Anchor strategy in the European Health Data Space

The EHDS is the structural answer to the US health-system data advantage. Universities should treat EHDS participation not as administrative compliance but as core research infrastructure, including appointing data-stewardship leadership at the dean level and funding interoperability engineering.

8.5 Forge complementary intra-European partnerships

Oxford, ETH Zurich, Karolinska, and KU Leuven offer complementary strengths — biomedical AI, engineering, clinical translation, and imaging respectively. Bilateral and consortium partnerships across these capabilities will produce more durable translational outputs than parallel duplication. Horizon Europe and the RAISE programme are the natural funding vehicles.

8.6 Develop clinician-scientist tracks at scale

The UCSF clinical informatics fellowship and bioinformatics PhD pipeline have no European equivalent at comparable scale. European medical schools should establish parallel tracks combining clinical training with computational methods, ideally with rotations through hospital-embedded AI evaluation units to ensure exposure to deployment realities, not only to research.

CHAPTER 9 · DISCUSSION

Clinical AI has crossed the threshold from research to operational practice. The deployments documented here — NYUTron's health-system language model, Sepsis Watch's six-year continuous operation, MIT Jameel's antibiotic discoveries — establish that the question is no longer whether AI will reshape medicine but how the reshaping will be governed and who will lead it.

The United States currently leads on translational throughput because its institutional architecture is unusually well suited to it: integrated academic medical centers, concentrated philanthropic capital, large federated data assets within single health systems, and a regulatory regime that permits early deployment under institutional oversight. None of these features describe original scientific advantage; they describe organizational advantage.

Europe's comparative advantages are durable and, in the long run, more strategically valuable: a regulatory framework that the rest of the world is now adopting, the largest federated health-data infrastructure under construction globally, and a medical culture oriented toward population-level outcomes and equity. The strategic task for European universities is to convert these advantages into translational throughput before US incumbents lock in the standards, the data partnerships, and the talent flows of the next decade.

Three risks merit explicit attention. First, the EU AI Act, while strategically valuable, can be operationally punitive for early-stage academic projects without dedicated compliance support; universities must invest in shared compliance infrastructure rather than expecting individual research groups to absorb the cost. Second, the EHDS is only as useful as institutional capacity to use it, and most European medical schools are under-resourced for the data engineering required. Third, the absence of integrated academic medical centers in most of continental Europe is a structural constraint that universities cannot solve unilaterally — sustained engagement with national health authorities is required.

CHAPTER 10 · CONCLUSION

Artificial intelligence is no longer a peripheral concern of academic medicine. Within a generation, the institutions that today lead in clinical AI translation — most of them American — will set the norms by which medical practice is governed and the curricula by which physicians are trained. Europe possesses the science, the regulation, and the data infrastructure to lead in turn. What European universities must now provide is the organizational seriousness — the integrated centers, mandatory curricula, validation pipelines, EHDS-anchored research strategies, intra-European consortia, and clinician-scientist pipelines — to convert structural advantages into translational leadership. The window for doing so is the next five years.

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