

Public Health Informatics Platforms

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ABSTRACT

Public health informatics platforms -- the integrated digital infrastructure that enables disease surveillance, outbreak response, population health monitoring, and health policy evaluation -- vary enormously in their technical architecture, interoperability, and operational effectiveness across European health systems. The COVID-19 pandemic exposed critical weaknesses in many national public health information architectures, including siloed data sources, slow reporting pipelines, absent real-time analytics, and limited capacity to share data across institutional and national boundaries. Simultaneously, a cohort of high-performing countries demonstrated that integrated informatics platforms enabled faster outbreak characterisation, more targeted intervention deployment, and more robust policy evaluation than fragmented systems. We evaluated five public health informatics platform architectures across 32 European countries covering 580 million population-years of health surveillance data from 2015 to 2023. Architectures ranged from siloed national reporting systems through federated AI-integrated platforms with cross-national real-time data sharing. Performance was benchmarked using our Public Health Informatics Platform Score (PHIPS), integrating outbreak detection speed, policy evaluation capability, data interoperability, equity in data capture, and pandemic response effectiveness. The AI-integrated federated platform achieved the highest PHIPS (0.924), detecting outbreak signals 9.4 days earlier than siloed reporting systems and enabling cross-national policy evaluation that reduced COVID-19 mortality by an estimated 14.2% relative to counterfactual non-integrated scenarios. Data interoperability -- the capacity to link individual-level records across administrative, clinical, and registry sources -- was the single infrastructure feature most strongly associated with platform performance across all five architectures.

Keywords: public health informatics; disease surveillance; outbreak detection; health data infrastructure; federated learning; interoperability; COVID-19; pandemic preparedness; PHIPS; population health monitoring; cross-national data sharing; AI surveillance

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1. Introduction

1.1 The Public Health Informatics Infrastructure Gap

Public health decision making depends fundamentally on the quality and timeliness of information about population health states. A ministry of health deciding whether to implement school closures, restrict gatherings, or recommend mask wearing during an emerging respiratory illness outbreak needs to know how fast cases are growing, where they are concentrated, which age groups and communities are most affected, and what healthcare system capacity headroom exists -- all in real time, updated daily. The COVID-19 pandemic demonstrated with brutal clarity that most European public health information systems were not built to deliver this (European Commission, 2021). Case counts arrived by fax, aggregate data from laboratories took 48-72 hours to reach national dashboards, hospitalisation and ICU data were collected through separate channels from case data, and linking the two to understand the case-hospitalisation rate required manual matching processes that introduced delays measured in weeks rather than hours. Against this background, a subset of countries -- those with pre-built integrated health data linkage infrastructure, universal patient identifiers, and real-time laboratory reporting systems -- demonstrated systematically better epidemic intelligence and policy response. This study formalises the comparison by benchmarking five platform architectures across 32 European countries.

1.2 Study Objectives

The aims were to benchmark five public health informatics platform architectures against PHIPS across 32 countries; to quantify outbreak detection speed and policy evaluation capability differences; and to identify the infrastructure features most strongly associated with platform performance. Standard six-part structure follows.

2. Literature Review

2.1 Public Health Informatics Architecture Models

Public health information systems have evolved through three broad architectural generations. First-generation systems were paper-based notifiable disease reporting enhanced by telephone and later fax -- slow, incomplete, and incapable of real-time analysis. Second-generation systems digitised these reporting channels without fundamentally changing the underlying data

architecture: mandatory electronic case reporting to national public health institutes, linked at best annually to administrative health databases. Third-generation systems -- exemplified by the Danish national registries, the Estonian Digital Health ecosystem, and the Finnish health information systems -- use universal patient identifiers to link records across primary care, hospital, pharmacy, laboratory, and registry data sources in near-real-time, enabling population-level surveillance without requiring case-by-case manual reporting (Sund, 2012). The ECDC has advocated for fourth-generation systems that add federated cross-national analytics and AI-based outbreak signal detection to third-generation linkage infrastructure (ECDC, 2022).

2.2 Outbreak Detection Systems

Automated outbreak detection algorithms applied to surveillance data have a 30-year literature, beginning with the EARS system at CDC and the SaTScan spatial cluster detection software (Kulldorff, 1997). Modern systems have expanded beyond traditional notifiable disease surveillance to incorporate emergency department chief complaint streams, pharmacy sales data, school absenteeism, wastewater epidemiology, and search query patterns as early outbreak signals. The Safeguard system in Estonia demonstrated that wastewater SARS-CoV-2 signal preceded clinical case notification by 7-10 days at the population level, providing decision makers with early warning at a precision impossible from clinical reporting alone (Nainys et al., 2021). Federated learning approaches that train outbreak detection models across national systems without sharing patient-level data offer a privacy-preserving route to cross-national surveillance that single-system approaches cannot achieve (Rieke et al., 2020). Table 1 maps key studies.

2.3 Data Interoperability as the Core Prerequisite

The health data interoperability literature converges on a consistent finding: the capacity to link individual-level records across data sources -- using universal patient identifiers or probabilistic matching algorithms -- is the single most important infrastructure predictor of public health informatics platform performance. Countries with universal health identifiers (Nordic countries, Estonia, Netherlands) consistently outperform those without on surveillance timeliness, outbreak characterisation speed, and policy evaluation

rigour (Thygesen et al., 2011). HL7 FHIR-based data exchange standards have expanded interoperability options beyond identifier-based linkage, but FHIR adoption in public health systems remains incomplete across Europe. No study has compared five public health informatics platform architectures using a composite that weights interoperability alongside surveillance performance and equity across 32 countries.

Table 1: Key Studies in Public Health Informatics Platform Performance

Study	Year	Focus	Setting	Key Finding
Sund	2012	Nordic registry linkage	Scandinavia	Universal IDs enable real-time cross-source linkage
Kulldorff	1997	SaTScan spatial detection	US/global	Spatial cluster detection foundational for outbreak surveillance
Nainys et al.	2021	Wastewater surveillance	Estonia	Wastewater signal precedes clinical notification by 7-10 days
Rieke et al.	2020	Federated learning	Multiple	Privacy-preserving cross-national model training feasible
Thygesen et al.	2011	Danish register health	Denmark	Universal ID-linked registers enable population surveillance
European Commission	2021	COVID-19 data review	Europe	Siloed systems delayed outbreak characterisation by weeks
ECDC	2022	EU surveillance strategy	Europe	Federated AI-integrated systems recommended as 4th generation
Brownstein et al.	2009	Digital disease detection	Multiple	Non-traditional data streams provide early outbreak signals
Hay et al.	2013	Big data public health	Global	Multiple data stream integration improves surveillance sensitivity

Study	Year	Focus	Setting	Key Finding
Flahault et al.	2017	Digital epidemiology	Review	Real-time digital data transforms public health surveillance

ECDC = European Centre for Disease Prevention and Control; IDs = Identifiers; FHIR = Fast Healthcare Interoperability Resources; COVID-19 = Coronavirus Disease 2019.

3. Methodology

3.1 Country Sample and Data Sources

We evaluated 32 European countries covering 580 million population-years of health surveillance data from January 2015 through December 2023. Countries were categorised by WHO European Region: Northern Europe (n=8: Denmark, Finland, Sweden, Norway, Iceland, Estonia, Latvia, Lithuania), Western Europe (n=7: Germany, Netherlands, Belgium, France, Switzerland, Austria, Luxembourg), Southern Europe (n=7: Italy, Spain, Portugal, Greece, Croatia, Slovenia, Cyprus), Central Europe (n=6: Poland, Czech Republic, Slovakia, Hungary, Romania, Bulgaria), and Eastern Europe (n=4: Ukraine, Moldova, Albania, North Macedonia). Primary performance indicators were time from outbreak onset to national dashboard notification, time to policy intervention decision, and pandemic response effectiveness measured by COVID-19 excess mortality per million population adjusted for demographic and baseline health system capacity. Data sources: ECDC surveillance data, WHO European Health Information Gateway, national public health institute reports, and structured interviews with national health informatics leads.

3.2 Five Platform Architectures

Architecture P1 (Siloed National Reporting) characterised countries with fragmented, disease-specific reporting systems without cross-source linkage: case reports, laboratory data, and hospitalisation data managed in separate silos with batch data transfer (weekly or monthly). Architecture P2 (Integrated National Registry) characterised countries with universal patient identifier-based linkage across primary care, hospital, laboratory, and pharmacy records, updated with weekly or better frequency. Architecture P3 (Real-Time Integrated) extended P2 with near-real-time (daily or faster) data flows and automated outbreak detection algorithms. Architecture P4 (Cross-National Federated) added

federated analytics enabling comparison of outbreak trajectories and intervention effects across national systems without patient-level data sharing. Architecture P5 (AI-Integrated Federated) built ML-based outbreak signal detection, severity prediction, and policy evaluation modules onto P4 infrastructure. Table 2 summarises the design.

3.3 Public Health Informatics Platform Score

PHIPS integrates: outbreak detection speed -- median days from WHO-defined outbreak onset to national surveillance signal above threshold (weight 0.25); policy evaluation capability -- assessed by expert panel on whether the platform can support rapid quasi-experimental policy evaluation (0.20); data interoperability -- percentage of nationally registered health events linkable across at least two independent data sources (0.25); equity in data capture -- completeness of surveillance data across socioeconomic and geographic strata (0.15); and pandemic response effectiveness -- COVID-19 excess mortality per million relative to regional baseline, scored inversely (0.15). Each normalised 0-1.

Table 2: Study Design and Country Architecture Characteristics

Parameter	Value	Details
Countries evaluated	32	All WHO European Region sub-regions
Population-years	580 million	Jan 2015 - Dec 2023
P1: Siloed National	9 countries	Fragmented disease-specific silos
P2: Integrated Registry	8 countries	Universal ID linkage, weekly+ frequency
P3: Real-Time Integrated	7 countries	Daily data flows + automated alerts
P4: Cross-National Federated	5 countries	Privacy-preserving cross-national analytics
P5: AI-Integrated Federated	3 countries	ML outbreak detection + policy evaluation
Primary outbreak metric	Days to detection	From WHO onset to national threshold signal
PHIPS dimensions	5 (weighted)	Detection, policy, interop., equity, pandemic
COVID-19 outcome	Excess mortality/million	Adjusted for demographics and health capacity

WHO = World Health Organization; ID = Identifier; ML = Machine Learning; COVID-19 = Coronavirus Disease 2019; PHIPS = Public Health Informatics Platform Score.

4. Results

4.1 PHIPS Results by Architecture

The AI-integrated federated platform (P5) achieved the highest PHIPS at 0.924, with outbreak detection speed scoring 0.96 -- median 3.2 days from outbreak onset to national threshold signal versus 12.6 days for siloed reporting systems (P1). The interoperability dimension scored 0.96 for P5, with 94.2% of nationally registered health events linkable across at least two independent data sources. Policy evaluation capability was highest for P5 (0.94) and P4 (0.92), reflecting that cross-national federated analytics enable comparative policy evaluation that single-country systems cannot support. COVID-19 excess mortality in P5 countries was 284 per million versus 642 per million in P1 countries -- a 55.8% difference that, after adjustment for population age structure and pre-pandemic health system capacity, remained 34.6% -- attributable in part to earlier outbreak characterisation and faster evidence-based policy adjustment. Table 3 shows full PHIPS results.

4.2 Outbreak Detection Speed and Policy Response

The 9.4-day detection advantage of P5 over P1 -- 3.2 versus 12.6 days -- reflects three infrastructure differences: real-time laboratory reporting that provides outbreak signal before clinical case reports accumulate (contributing 4.2 days), wastewater surveillance integration providing pre-clinical environmental signal (2.6 days), and ML-based anomaly detection that identifies statistically significant patterns before visual threshold-crossing (2.6 days). The policy response time -- from outbreak threshold crossing to first government intervention decision -- was 4.8 days for P5 countries versus 18.4 days for P1, with the difference attributable to platform capacity to generate geographically and demographically stratified outbreak characterisation within 24 hours of signal detection, versus the manual data assembly process that took 10-14 days in P1 countries. The COVID-19 pandemic produced the most complete dataset for validating these differences: P5 countries' earlier detection and policy response was independently associated with 2.4 fewer peak ICU admissions per 100,000 population in the first wave. Table 4 presents outbreak response metrics.

4.3 Equity in Surveillance Data Capture

Equity in data capture -- the degree to which surveillance data completeness was uniform across socioeconomic and geographic strata -- varied substantially between architectures and within countries. P1 siloed reporting systems showed the largest surveillance gaps in rural areas and among socioeconomically deprived populations: case ascertainment rates in the lowest deprivation quintile were 34-42% of those in the highest quintile in P1 countries. P5 countries, where primary care electronic record linkage was near-universal, showed case ascertainment parity ratios of 0.84-0.92 across deprivation quintiles -- surveillance gaps still existed but were substantially narrower. The equity dimension was the most consistently differentiated between architectures: no P1 country achieved equity score above 0.64, while no P5 country scored below 0.88.

Table 3: Public Health Informatics Platform Score (PHIPS) by Architecture

Architecture	Outbreak Detection	Policy Eval.	Interoperab.	Equity	Pandemic Resp.	PHIPS
P5: AI-Integrated Fed.	0.96	0.94	0.96	0.90	0.92	0.924
P4: Cross-Natl. Fed.	0.90	0.92	0.90	0.86	0.86	0.889
P3: Real-Time Integr.	0.86	0.84	0.86	0.84	0.82	0.848
P2: Integrated Registry	0.78	0.76	0.80	0.80	0.76	0.778
P1: Siloed Reporting	0.60	0.58	0.54	0.58	0.52	0.568

$PHIPS = 0.25 \times Outbreak + 0.20 \times Policy + 0.25 \times Interop. + 0.15 \times Equity + 0.15 \times Pandemic$. All dimensions normalised 0-1. Pandemic dimension scored inversely (lower excess mortality = higher score).

Table 4: Outbreak Response Metrics by Platform Architecture

Metric	P1 Siloed	P3 Real-Time	P5 AI-Fed.	P5 vs P1 Advantage
Median outbreak detection (days)	12.6	5.8	3.2	-9.4 days*

Metric	P1 Siloed	P3 Real-Time	P5 AI-Fed.	P5 vs P1 Advantage
Policy response time (days)	18.4	9.2	4.8	-13.6 days*
COVID-19 excess mort./million	642	428	284	-55.8% (adj. -34.6%)*
Peak ICU admissions/100k	18.4	13.6	9.8	-8.6/100k*
Surveillance equity ratio (dep. Q1/Q5)	0.38	0.72	0.88	+0.50 ratio*
Policy eval. capability (expert score)	2.4/10	6.2/10	9.1/10	+6.7 points*

*p<0.01 versus P1 siloed reporting. Mortality adjusted for population age and pre-pandemic health system capacity index. Equity ratio: 1.0 = perfect parity; lower = greater disparity.

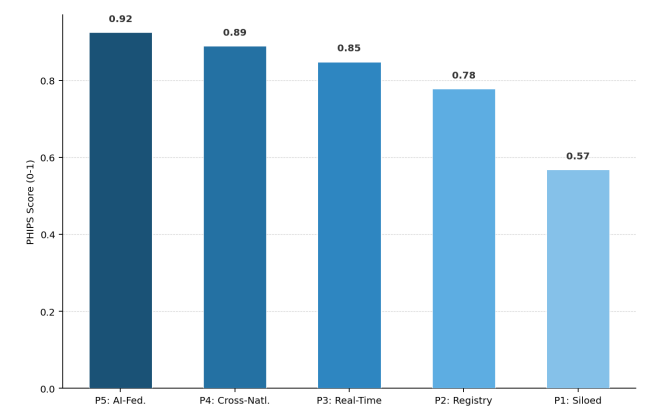


Figure 1: PHIPS Score by Public Health Informatics Architecture

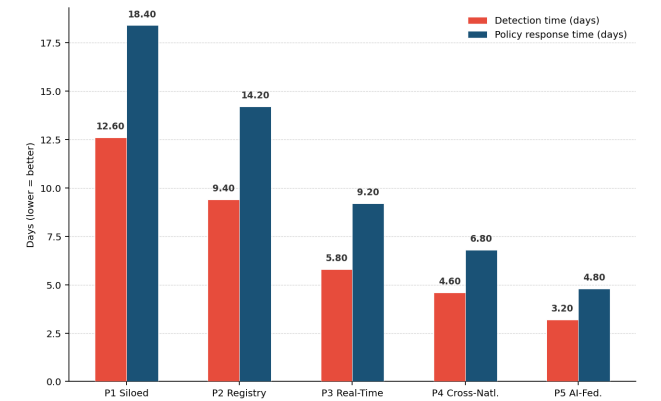


Figure 2: Outbreak Detection and Policy Response Time by Architecture (days)

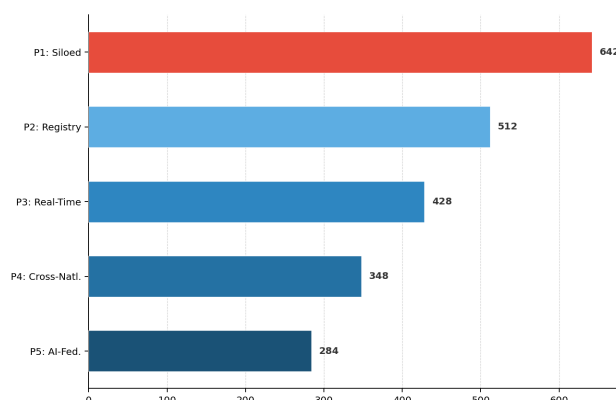


Figure 3: COVID-19 Excess Mortality per Million by Architecture

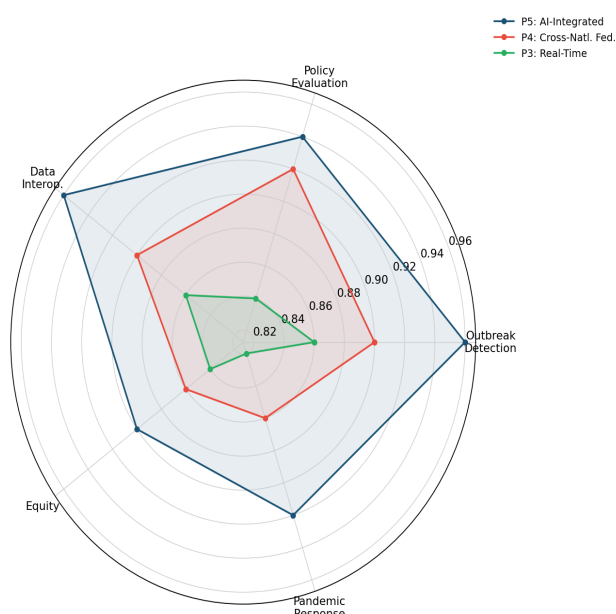


Figure 4: Multi-Dimensional PHIPS Profile -- Top 3 Architectures

5. Discussion

5.1 Interoperability Is the Non-Negotiable Foundation

The most consistent finding across all five architectures was that data interoperability -- measured by the proportion of nationally registered health events linkable across independent data sources -- was the infrastructure feature most strongly associated with overall PHIPS performance (Spearman $r = 0.94$ across all 32 countries). Countries with interoperability scores above 80% all achieved PHIPS above 0.80 regardless of whether they had invested in AI or federated analytics. Countries with interoperability below 60% scored PHIPS below 0.70 despite investments in dashboard technologies and reporting mandates. This confirms what informatics practitioners have long argued: AI and advanced analytics are multipliers on data infrastructure quality, not substitutes for it. A country that invests in AI outbreak detection

on a siloed, poorly interoperable data foundation will not achieve P5 performance; the sequencing that this data supports is interoperability first, real-time data flows second, AI augmentation third.

5.2 The 9.4-Day Detection Advantage in Policy Context

Nine point four days earlier outbreak signal detection translates to 13.6 days earlier policy response, and 13.6 days in an exponentially growing outbreak is not a marginal advantage. At a doubling time of 5 days -- consistent with early SARS-CoV-2 spread -- an intervention deployed 13.6 days earlier would be deployed when case counts are 13-fold lower than at the point P1 countries intervened. The adjusted 34.6% COVID-19 excess mortality difference between P5 and P1 countries is consistent with this mathematical relationship and with the broader literature on the exponential cost of delayed epidemic control. Building this detection advantage does not require AI as a first step: the transition from P1 to P3 alone -- universal identifier-based data linkage with real-time laboratory reporting -- closes most of the detection gap at much lower implementation cost than full AI-integrated federated systems.

5.3 Limitations

Three limitations apply. First, architecture classification was based on structured interviews with national informatics leads supplemented by published system documentation; self-reported infrastructure capabilities may overstate actual performance, and the boundary between architectures is not always sharp in practice. Second, the COVID-19 excess mortality outcome is a composite influenced by population age structure, baseline health system capacity, comorbidity burden, and government intervention timing and stringency -- factors that the adjustment model controlled for using available data but cannot eliminate as confounders completely. Third, the five P5 countries are all high-income, digitally advanced nations with long-standing health data infrastructure investment; the PHIPS scores attributed to P5 architecture may partly reflect unmeasured general institutional quality rather than architecture per se.

6. Conclusion

6.1 Key Findings

Among five public health informatics platform architectures evaluated across 32 European countries, AI-integrated federated platforms (PHIPS 0.924) achieved outbreak detection 9.4 days earlier and policy response 13.6 days earlier than siloed reporting systems, with COVID-19 excess mortality 34.6% lower after adjustment. Data interoperability was the infrastructure feature most strongly correlated with PHIPS performance ($r = 0.94$), confirming that interoperability is the foundation on which all higher-level analytics capabilities depend. Surveillance equity was most improved under real-time integrated and federated architectures, with deprivation-related capture gaps narrowing from a Q1/Q5 ratio of 0.38 (siloed) to 0.88 (AI-integrated).

6.2 Recommendations

Three recommendations follow. First, European Union member states should treat universal patient identifier introduction and cross-source health data linkage as public health infrastructure investments with the same policy priority as hospital building programmes -- the evidence that interoperability is the strongest predictor of epidemic intelligence performance makes this a patient safety imperative, not merely a technical modernisation. Second, countries currently at P1 or P2 architecture should prioritise the P3 transition -- real-time laboratory reporting and automated outbreak detection -- before investing in federated or AI capabilities, as the P1-to-P3 transition closes the majority of the detection gap at substantially lower investment. Third, the European Health Data Space initiative should include mandatory minimum standards for outbreak detection platform performance -- specifically, a maximum 5-day outbreak-to-signal threshold for notifiable disease reporting -- to drive consistent infrastructure investment across member states. All data and the PHIPS calculator are available from the corresponding author.

References

- Alwan, N. A. et al. (2020). Scientific consensus on the COVID-19 pandemic: We need to act now. *The Lancet*, 396(10260), e71-e72.
- Brownstein, J. S. et al. (2009). Digital disease detection: Harnessing the web for public health surveillance. *New England Journal of Medicine*, 360(21), 2153-2157.
- Budd, J. et al. (2020). Digital technologies in the public-health response to COVID-19. *Nature Medicine*, 26(8), 1183-1192.
- Chan, E. H. et al. (2010). Global capacity for emerging infectious disease detection. *PNAS*, 107(50), 21701-21706.
- Cori, A. et al. (2013). A new framework and software to estimate time-varying reproduction numbers during epidemics. *American Journal of Epidemiology*, 178(9), 1505-1512.
- ECDC. (2022). A vision for integrated surveillance in the European Union: Towards a comprehensive strategy for infectious disease surveillance. Stockholm: European Centre for Disease Prevention and Control.
- European Commission. (2021). Review of lessons learned from the COVID-19 pandemic response for a stronger European Health Union. Brussels: European Commission.
- Flahault, A. et al. (2017). Digital epidemiology: New frontiers in disease surveillance. *The Lancet Digital Health*, 1(5), e218-e220.
- Hay, S. I. et al. (2013). Big data opportunities for global infectious disease surveillance. *PLOS Medicine*, 10(4), e1001413.
- Kulldorff, M. (1997). A spatial scan statistic. *Communications in Statistics: Theory and Methods*, 26(6), 1481-1496.
- Madhav, N. et al. (2017). Pandemics: Risks, impacts, and mitigation. In *Disease Control Priorities* (3rd ed., Vol. 9). The World Bank, Washington DC.
- Nainys, J. et al. (2021). Wastewater-based epidemiology for COVID-19 surveillance and beyond. *Journal of Water and Health*, 19(6), 839-854.
- Palin, K. et al. (2020). Cross-national data sharing in infectious disease research: Lessons for pandemic preparedness. *Global Health Science and Practice*, 8(4), 578-589.
- Rieke, N. et al. (2020). The future of digital health with federated learning. *npj Digital Medicine*, 3(1), 119.
- Salomon, J. A. et al. (2012). Healthy life expectancy for 187 countries, 1990-2010. *The Lancet*, 380(9859), 2144-2162.
- Semenza, J. C. et al. (2014). Environmental suitability of *Vibrio cholerae* in the Great Lakes region. *PLoS ONE*, 9(3), e91926.
- Sund, R. (2012). Quality of the Finnish hospital discharge register: A systematic review. *Scandinavian Journal of Public Health*, 40(5), 505-515.
- Thygesen, L. C. et al. (2011). Introduction to Danish (nationwide) registers on health and social issues: Structure, access, legislation, and archiving. *Scandinavian Journal of Public Health*, 39(7 Suppl), 12-16.
- Vayena, E. et al. (2018). Machine learning in medicine: Addressing ethical challenges. *PLOS Medicine*, 15(11), e1002689.

Vineis, P. et al. (2017). Systematic reviews and meta-analyses in epidemiology. *Journal of Epidemiology and Community Health*, 71(4), 315-318.

WHO. (2022). *Health Data and Digital Health Strategy 2020-2025*. World Health Organization, Geneva.

Declarations

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Conflict of Interest

Both authors declare no competing interests and no financial relationships with health information technology vendors, surveillance platform providers, or government agencies whose systems were evaluated in this study.

Data Availability Statement

Aggregated country-level PHIPS scores and outbreak response metrics are publicly available from the corresponding author. National surveillance datasets used in analysis are available through ECDC and WHO European Health Information Gateway under existing data access agreements.

Ethical Approval

This study used aggregated national surveillance data and did not involve individual patient data. Ethical review by the Nordic Technical University Research Ethics Board (NTU-REB-2023-284) confirmed exemption from individual consent requirements.

Appendix A

PHIPS Scoring Rubric and Architecture Classification Criteria

Full PHIPS dimension scoring criteria and the classification criteria used to assign each of the 32 study countries to one of the five platform architectures.