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Int. J. Clin. Res. Med. Sci. (2026) 1(3):1–21
Article ID: IJCRMS-2026-969

Public Sector Analytics for Territorial Healthcare Planning: Federated Learning Under the European Health Data Space

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Abstract

This paper applies public sector analytics to the challenges of demographic decline, population ageing, and progressive desertification of healthcare and social care services in many European territories. These trends threaten territorial cohesion and equitable access to care. The European Health Data Space (EHDS) establishes a new regulatory and infrastructural framework for primary and secondary use of health data across Member States, opening opportunities for advanced analytics under strict data protection safeguards. This paper argues that federated learning (FL), embedded within the EHDS governance framework, has the potential to serve as a policy data infrastructure to support territorial healthcare planning in ageing and shrinking regions. Public sector analytics components include long-term care demand forecasting, healthcare service availability indices, territorial inequality measurement, cross-regional benchmark comparisons, and policy intervention readiness scoring. Rather than focusing on algorithmic performance, we develop a conceptual model linking FL-enabled distributed analytics to concrete policy questions on care demand, service availability, and territorial inequalities in access. We first map the information needs of policy-makers dealing with demographic change and territorial cohesion, then analyse how EHDS provisions on secondary use, Health Data Access Bodies, and privacy-enhancing technologies can underpin multi-territorial FL projects. Building on this analysis, we propose a policy-oriented framework describing actors, processes, and outputs of EHDS-compliant FL initiatives aimed at informing regional and national health and social care strategies. We discuss implications for territorial cohesion, sustainability of health systems, and future research on governance of federated learning in European health data spaces.

Keywords

• Public Sector Analytics • Federated Learning • European Health Data Space (EHDS) • Healthcare Planning • Population Ageing • Territorial Cohesion • Health Data Governance • Secondary Use of Health Data

1. Introduction

The changes in age and marital status on the European continent will test their health and social care systems [1][2]. Despite urban areas growing, rural, fringe and inner areas are not only declining, but they are also ageing faster. These differences lead to a shrinking local tax base, rising old-age dependency ratios, and increased challenges to maintaining concentrated health and social care services [3]. In a number of Member States, this leads to “medical desertification,” characterised by a lack of general practitioners, closure or downgrading of small hospitals, and greater distances and longer travel times to access necessary health services.

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As such, territorial inequalities in access to care have become a major concern of health as well as cohesion policies [4]. People living in areas with fewer people and older population groups often have to face higher barriers to timely diagnosis and treatment, less availability of long-term care options and greater reliance on informal care arrangements [5]. Regional and local health authorities cannot plan and fund services in small, dispersed populations where achieving economies of scale is difficult and traditional hospital-centred models of care are not sustainable. Decision-makers in Europe, nationally and regionally rely on fragmented, siloed and poorly interoperable data which is often limited to the institutional and regional boundaries and, in turn, hampers their ability to anticipate future needs and assess the territorial impact of reforms [6].

The EHDS Regulation lays down a new regulatory and infrastructural framework for the primary and secondary use of electronic health data in the member states. It is explicitly aiming to promote research, innovation and evidence-informed health policy [7]. Simultaneously, federated learning (FL) has emerged as a distributed analytical framework that keeps health data under the control of local data holders while allowing multi-centre models to be trained. While FL provides a degree of data localisation that can facilitate compliance with data protection requirements, it should be emphasised that FL does not inherently ensure privacy or prevent disclosure. Model updates and outputs remain susceptible to various privacy attacks, including gradient inversion [8], membership inference [9, 10], and attribute inference [10]. Achieving meaningful privacy guarantees within FL deployments typically requires additional technical safeguards such as secure aggregation [11], differential privacy [12], and rigorous access controls [13]. This paper argues that EHDS combined with FL can be conceived as a policy data infrastructure for territorial health planning in ageing and shrinking regions that could potentially provide previously unavailable analytics capabilities in the public sector, subject to empirical validation [6].

This study adopts a public sector analytics perspective to explore how federated learning within the EHDS could potentially support regional healthcare planning. It conceptualises public sector intelligence as an active, dynamic capability rather than a static policy report, embedded within modern governance architectures. A primary contribution of this work is the development of a policy-oriented framework for applying distributed analytics to territorial healthcare challenges. Current approaches often rely on statistical simplifications or computationally expensive numerical techniques that are unsuitable for interactive policy analysis. Furthermore, many existing systems incorporate oversimplified assumptions that fail to capture the complex territorial dynamics of healthcare provision [5]. The framework is presented as a conceptual/design framework proposing how EHDS-enabled federated analytics could support territorial healthcare planning, rather than as evidence that the proposed architecture actually works.

1.1 Methodological Approach

This paper develops its conceptual framework through a structured analytical synthesis of three intersecting bodies of literature and policy documents: (1) peer-reviewed research on federated learning in healthcare and public sector applications, (2) the EHDS Regulation and associated European Commission guidance documents, and (3) territorial health planning literature addressing demographic decline and service accessibility. The framework development followed an iterative process of: (a) identifying policy-relevant analytical components from territorial planning literature and practitioner needs, (b) mapping EHDS regulatory requirements to FL technical and governance features, (c) deriving actor categories and lifecycle stages through analysis of governance responsibilities in EHDS-compliant secondary-use projects, and (d) synthesising these elements into a coherent policy-oriented framework. This approach is consistent

with design-science reasoning for conceptual frameworks in public policy contexts, where the aim is to construct an artefact that bridges regulatory requirements and practical implementation needs. The framework is presented as a testable conceptual model requiring empirical validation through pilot implementations.

This paper makes four main contributions to the literature on public sector analytics for territorial healthcare planning. First, it provides a comprehensive mapping of how federated learning, as a privacy-enhancing analytical paradigm, can be operationalised within the regulatory and institutional framework of the European Health Data Space. Second, it develops a policy-oriented framework that identifies the key actors, processes, and outputs necessary for EHDS-compliant FL projects specifically targeted at regions facing demographic decline and ageing populations. The framework is proposed as a conceptual/design artefact and is intended to identify how FL could potentially support territorial healthcare planning, subject to empirical validation. Third, it articulates a set of public sector analytics components including long-term care demand forecasting, service availability indices, territorial inequality measurement, and policy intervention readiness scoring that could potentially address the information needs of policy-makers concerned with healthcare access inequality and territorial cohesion. The proposed framework identifies how FL could potentially support these analytical capabilities, subject to empirical validation. Fourth, it discusses the governance implications and implementation challenges of deploying FL as a policy data infrastructure, with particular attention to capacity inequalities, stakeholder trust, and cross-border coordination. By integrating these elements, the paper bridges the gap between technical FL research and public health policy, offering a conceptual foundation for evidence-informed territorial planning in an ageing Europe.

2. Related Work and Policy Context

Federated learning is gaining momentum in healthcare as a distributed analytical approach that enables multi-centre analysis without requiring raw data to be centralised, allowing institutions to retain control over their local data while operating within data protection regulation requirements. However, FL should not be considered inherently privacy-preserving: model updates, gradients, and aggregated outputs can leak information about individual training examples through various inference attacks, and additional safeguards are typically required to provide formal privacy guarantees [8–10]. Systematic reviews show that FL applications are rapidly expanding across diverse domains including oncology, radiology, and chronic disease management. However, they also report technical and organisational challenges including data clarity, communication efficiency, and evaluation. A large majority of FL healthcare studies have limited real-world applicability. Furthermore, sustained production deployment remains limited. This is due to the presence of hardware heterogeneity and non-IID data that acts as a primary barrier [14]. There is at least one major exception, namely the EXAM COVID-19 multi-centre study, showing that large-scale FL in health care is possible when governance and technical conditions are met.

Simultaneously, researchers have started looking at the governance of FL in health care. As per the scoping reviews and conceptual framework, it is clear that federated approaches will need different governance mechanisms to centralised machine learning like new procedural, relational and structural arrangements [13]. The frameworks proposed make it clear that the ethical issues, fairness, accountability, and risk of harm require clarity of roles and responsibilities, formal agreements, oversight structures, and stakeholder engagement [4]. Nonetheless, limited and fragmented is empirical evidence on how these governance models operate in practice. Governance of federated learning can be regarded as a critical aspect that needs to be addressed before its public sector deployment [7].

The emerging literature on the European Health Data Space argues that it can help to overcome the current fragmentation of health data present in Europe while balancing the opportunities for reuse of health data with risks to privacy and fundamental rights [15]. According to the authors, the EHDS clearly acknowledges privacy-enhancing technologies as well as federated systems as tools for implementing secure secondary use under the supervision of Health Data Access Bodies and in secure processing facilities [13]. In contrast, readiness for implementation varies widely between Member States, with the Nordic nations benefiting from considerable HDAB capacity-building. Timelines for data access vary from a few weeks to more than a year. Recent work on cloud-enabled enterprise data warehouse architectures has demonstrated how regional health resource optimization and insurance analytics can be supported through distributed data infrastructures, providing relevant precedents for EHDS-compliant analytics [16]. Furthermore, advances in model-driven engineering for health data management in large-scale clinical research have shown how clinical data can be integrated and reused with automated software solutions, offering technical foundations for the framework proposed in this paper [17].

Beyond governance and infrastructure, several studies have addressed privacy and security challenges in health data analytics. Research on digital safeguards for health data has architected privacy and security mechanisms for next-generation medical informatics [18]. Similarly, work on information security and privacy-preserving federated learning for collaborative healthcare diagnosis has developed technical approaches directly relevant to the FL paradigm discussed here [19]. Studies on patient-controlled health data management through blockchain integration have proposed prototype approaches that complement the governance mechanisms envisioned under the EHDS [20].

In the domain of public health analytics, research has addressed practical challenges of data quality and completeness. Work on stabilizing epidemic surveillance has developed scalable frameworks for real-time correction of incomplete public health data [21]. Related research has examined data-driven optimization of practitioner panel sizes for population-centric healthcare delivery, providing methodological insights applicable to territorial health planning [22]. Additionally, studies on enhancing allied health service delivery in underserved areas through strategic planning interventions have addressed challenges directly relevant to the medical desertification problem motivating this paper [23].

The application of AI and predictive analytics in healthcare has also progressed significantly. Research on tracking temporal variations in predictive models for healthcare claims data has addressed the challenge of model stability over time, which is particularly relevant for long-term care demand forecasting [24]. Work on artificial intelligence-enhanced telemedicine has explored how AI can transform diagnosis and personalized care in virtual health systems, offering potential complements to territorial planning frameworks [25]. Furthermore, methodological advances in functional data analysis have developed approaches for basis selection and truncation optimization in scalar-on-function regression, providing statistical foundations for the analytical components proposed in this paper [26].

Despite laying important foundations, these strands of research have at least two gaps which this paper fills. First, previous research on FL in healthcare and public health does not consider demographic decline, territorial cohesion, and inequalities in access to care as primary lenses, rather focusing on clinical or disease-specific use cases [6]. Furthermore, unlike the earlier sections, most of the conversations on EHDS and PETs remain quite vague. No one has tried to clarify or even spell out how federated learning can be operationalised as policy data infrastructure [5]. In addition, federated learning can be very useful for territorial health planning within the governing framework of EHDS [14]. Some prior work has suggested that privacy guarantees in FL systems may incur only modest accuracy penalties under certain conditions. However, these findings are specific to particular datasets, model architectures, and FL configurations, and should not be generalised to the diverse contexts of territorial health planning. The computational

overhead and utility implications of achieving EHDS compliance through FL and PETs remain empirical questions that depend on factors including data heterogeneity, model complexity, the specific privacy techniques employed, and the scale of deployment. This paper therefore treats such claims as hypotheses requiring validation through pilot implementations rather than as established findings applicable to the framework.

3. The European Health Data Space as Regulatory Infrastructure

The EHDS Regulation (Regulation (EU) 2025/327) establishes a common framework for the use and exchange of electronic health data across the European Union, with the dual objective of empowering individuals through improved access to and control over their health data (primary use) and enabling secure data reuse for research, innovation, and policy-making (secondary use). It seeks to overcome the current fragmentation of health data landscapes by harmonising legal and technical conditions for data access, interoperability, and quality, while preserving strong protections for privacy and data protection as established under the General Data Protection Regulation (GDPR). The Regulation represents a landmark initiative that fundamentally reshapes the European health data governance landscape. The provisions for secondary use are set out in Title IV of the Regulation, with detailed requirements for data access, processing, and governance to be further specified through implementing and delegated acts.

For secondary use, the EHDS creates a secure, consistent, and trustworthy framework that allows electronic health data to be reused for specified purposes, including health-related scientific research, training and testing of algorithms, and policymaking in the healthcare sector. Under Article 34 of the Regulation, Member States must designate Health Data Access Bodies (HDABs) as competent authorities for secondary use. These bodies serve as gatekeepers: they receive and assess applications from data users, issue data permits, and ensure that data processing takes place in secure processing environments as specified in Article 41. Data holders are required to make in-scope datasets available for secondary use under the conditions specified in data permits, which may include requirements for anonymisation or pseudonymisation and restrictions on data downloading, as set out in Articles 39-40 of the Regulation.

From the viewpoint of territorial health planning, the EHDS is particularly relevant because it enables cross-organisation and cross-border analyses under a shared governance regime. Articles 44-46 of the Regulation establish the HealthData@EU infrastructure to support cross-border projects, with the European Commission facilitating coordination among Member States. Interoperability requirements (Title V) and common data categories (Annex I) facilitate the combination of data from different regions and providers, though implementation timelines and technical specifications are subject to further delegated and implementing acts. The Regulation does not prescribe specific analytical architectures, allowing for different technical approaches including centralised data warehouses, data enclaves, and distributed analytical methods such as federated learning, provided they comply with the conditions set out in data permits and secure processing requirements (Articles 40-42).

This openness creates space to explore FL as a distributed, policy-oriented way of exploiting EHDS-enabled data resources. The EHDS provides the regulatory and governance framework; FL is a proposed technical architecture that may operate within that framework. The EHDS framework provides the legal and institutional layer through HDABs, data permits, secure processing environments, and standardised data specifications (as defined in the Regulation and its implementing acts), while FL provides a possible analytical mechanism to exploit distributed data sources for policy purposes. The convergence of a regulatory framework under development and a promising analytical paradigm creates an opportunity for evidence-informed territorial health planning, subject to compliance with applicable provisions and the

completion of implementing measures.

3.1 Established EHDS Provisions versus Proposed Implementation Models

It is important to distinguish between provisions explicitly established by the EHDS Regulation, elements established through implementing/delegated acts, elements proposed by the authors as a suitable governance or implementation model, and elements that are merely possible FL implementations.

Established EHDS requirements include: the obligation for Member States to establish Health Data Access Bodies (HDABs) as competent authorities for secondary use; the requirement for data permits to be time-limited and purpose-bound; the mandate for secure processing environments for data analysis; the obligation for data holders to make in-scope datasets available for secondary use; and the interoperability and data quality specifications defined in the Regulation and implementing acts.

Established through implementing/delegated acts include: detailed requirements for data access, processing, and governance as further specified through implementing and delegated acts; technical specifications for interoperability and data quality; and procedural requirements for HDAB operations.

Proposed implementation elements include: the specific four-actor governance model (policy sponsors, HDABs, data holders/FL participants, and analytical coordinators); the five-stage project lifecycle; the use of federated learning as the analytical architecture; the specific public sector analytics components (demand forecasting, service availability indices, territorial inequality measurement, benchmarking, and readiness scoring); and the proposed allocation of responsibilities across actor groups.

Possible FL implementations include: the specific technical components (local clients, model aggregation and coordination server, secure processing environment, identity and access management, audit and logging, privacy-enhancing technologies, output dissemination) and the specific FL algorithms and protocols that could be used within the EHDS framework.

The EHDS Regulation does not mandate FL or prescribe specific analytical architectures; rather, it provides a regulatory and institutional framework within which various technical approaches, including FL, may be implemented subject to compliance with data permit conditions and secure processing requirements. EHDS provides the regulatory and governance framework; FL is a proposed technical architecture that may operate within that framework.

3.2 The Distinct Roles of EHDS and Federated Learning

It is essential to clarify that the EHDS provides a legal, institutional, and technical *governance framework* for secondary use of health data, whereas FL is one possible *technical and analytical mechanism* that may operate within that framework. EHDS provides the regulatory and governance framework; FL is a proposed technical architecture that may operate within that framework. The EHDS Regulation does not mandate FL as the analytical architecture for territorial healthcare planning or any other secondary-use purpose. Rather, the Regulation establishes the conditions under which health data may be accessed and processed, including requirements for secure processing environments, data permits, and governance through HDABs, while leaving the choice of analytical architecture to data users, subject to compliance with these conditions. FL represents a specific distributed analytical paradigm that is particularly suited to scenarios where data cannot be centrally pooled due to legal, technical, or organisational constraints. Within the EHDS context, FL could be implemented as one means of conducting analyses across distributed data sources without requiring raw data transfers, provided that the specific implementation meets the conditions specified in the relevant data permit and secure processing requirements. The framework proposed in this paper therefore treats FL as a *potential* analytical approach within the EHDS

governance environment, rather than as a requirement of the Regulation itself.

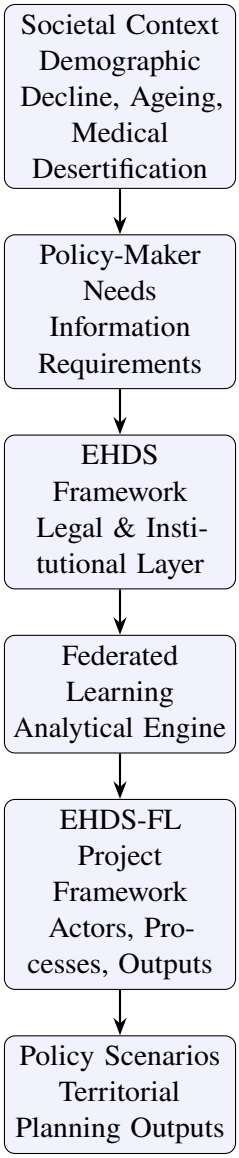


Figure 1: End-to-End Policy Data Infrastructure: EHDS and Federated Learning for Territorial Healthcare Planning

4. Proposed Framework for EHDS-Compliant Federated Learning Projects

This section presents a conceptual framework for the design and governance of FL initiatives within the EHDS framework for territorial health planning. The framework emphasises actors, processes, and outputs rather than technical architectures. The framework identifies how FL could potentially support territorial healthcare planning capabilities, subject to empirical validation. Table 1 provides a mapping between regulatory requirements, FL governance needs, and the resulting framework components.

The policy questions, choice of targeted territory, and overall strategy and resources are laid down by policy sponsors: for example, ministries of health, regional health authorities, cohesion policy bodies. HDABs assess proposals according to legal and ethical requirements, grant data permits, and oversee conditions of data use. Regional health authorities, hospitals, primary care organisations, and social care agencies control relevant datasets and run local FL components. Coordinators of analytical work,

including public health institutes and competence centres, design the FL studies, coordinate training rounds, and synthesise outputs into policy-oriented results.

Effective projects require a clear division of responsibilities and mutual trust, as well as adequate technical and organisational capacity. The framework emphasises that the EHDS will embed FL in institutional processes, not a stand-alone technical solution. Data permits are time-limited and purpose-bound, placing limitations on the scope of FL projects, while policy cycles impose deadlines that the analytical process must honour.

The four actor groups (policy sponsors, HDABs, data holders/FL participants, and analytical coordinators) were selected through analysis of governance responsibilities in EHDS-compliant secondary-use projects, as specified in the EHDS Regulation and associated guidance documents. Policy sponsors correspond to the entities responsible for defining policy questions and authorising projects; HDABs are established by the Regulation as competent authorities for secondary use; data holders/FL participants correspond to the entities required to make in-scope datasets available under the Regulation; and analytical coordinators correspond to the entities responsible for designing and executing analyses within secure processing environments. The five lifecycle stages (problem formulation, project design and authorisation, distributed analysis, synthesis and interpretation, policy uptake and feedback) were derived through analysis of the procedural requirements for secondary-use projects under the EHDS framework, including the data permit process, secure processing requirements, and the obligation for data holders to make datasets available. These stages represent a proposed conceptual lifecycle for EHDS-compliant FL projects, derived from regulatory requirements and governance best practices, rather than an empirically validated lifecycle. The framework is a proposed conceptual framework and has not been validated through expert validation, Delphi study, stakeholder interviews, comparative case studies, real EHDS pilots, simulated FL deployments, expert scoring, or framework evaluation. Such validation remains future work.

4.1 Minimum Technical Components for EHDS-Compliant FL

Although this paper focuses on governance rather than technical implementation, the proposed conceptual framework identifies a minimum set of technical components that could potentially be required for EHDS-compliant FL deployment, subject to empirical validation. These components are proposed as a conceptual design artefact and have not been validated through expert validation, Delphi study, stakeholder interviews, comparative case studies, real EHDS pilots, simulated FL deployments, expert scoring, or framework evaluation:

- **Local clients**: Deployed at each participating data holder's secure processing environment, performing local model training, computing model updates, and communicating with the coordination server without exposing raw data.
- **Model aggregation and coordination server**: Managed by the analytical coordinator, initialising the global model, distributing it to clients, aggregating received updates, and managing iterative training rounds.
- **Secure processing environment**: All data processing and model training must occur within environments meeting EHDS requirements (Article 41) for access control, logging, and data protection.

- **Identity and access management**: A system for authenticating and authorising all participants, aligning with HDAB identity verification requirements.
- **Audit and logging**: Comprehensive logging of all data access, training activities, and output generation for EHDS compliance.
- **Privacy-enhancing technologies**: Safeguards such as secure aggregation, differential privacy, and cryptographic protocols appropriate for the threat model.
- **Output dissemination**: A mechanism for converting aggregated results into policy-relevant outputs while ensuring no privacy-sensitive information is released.

4.2 Allocation of Governance and Accountability Responsibilities

The proposed framework establishes a proposed allocation of responsibilities across the four actor groups for key governance functions that could potentially be required for EHDS-compliant FL deployment, subject to empirical validation. Table 1 specifies proposed responsibilities for model validation, data quality, privacy risk, cybersecurity, model updates, error handling, auditability, and policy decisions based on model outputs.

Table 1: Allocation of Governance Responsibilities Across Actor Groups

Governance Function	**Policy Sponsors**	**HDABs**	**Data Holders/FL Participants**	**Analytical Coordinators**
Model validation and performance monitoring	Provide policy relevance criteria	Ensure regulatory compliance	Contribute local validation data	Conduct technical validation and performance evaluation
Data quality assurance	Define required data quality standards	Oversee data quality through permit conditions	Ensure local data quality; implement data preparation	Coordinate data quality assessment across participants
Privacy risk management	Define acceptable risk thresholds	Assess and approve privacy safeguards	Implement local privacy controls	Design privacy-preserving FL protocols
Cybersecurity	Provide cybersecurity policy framework	Set secure processing requirements	Maintain local secure processing environments	Ensure secure aggregation and coordination
Model updates and versioning	Authorise model changes	Ensure updates comply with permits	Implement local model updates	Manage model versioning and deployment
Error handling and incident response	Define escalation procedures	Oversee incident reporting	Report local errors; implement safeguards	Coordinate error detection and resolution
Auditability and documentation	Define audit requirements	Conduct audits; maintain permit records	Maintain local audit logs	Maintain audit trail of FL operations
Policy decisions based on outputs	Ultimate decision-making authority	Ensure decisions comply with legal framework	Provide local interpretation context	Translate analytical outputs into policy-relevant information

This allocation follows the principle that accountability should rest with the actor best positioned to exercise control and provide oversight for each specific function, while ensuring appropriate checks and balances.

4.3 Mapping Actors to Lifecycle Stages: A RACI Framework

Table 2 provides a RACI (Responsible, Accountable, Consulted, Informed) matrix mapping the four actor groups to the five lifecycle stages.

The lifecycle of an EHDS-compliant FL project proceeds through five stages: Problem formulation, where policy sponsors articulate a territorial challenge; Project design and authorisation, involving analytical coordinators designing the project and submitting to HDABs for data permits; Distributed analysis, with data holders preparing data and executing FL training rounds in secure environments; Synthesis and interpretation, where coordinators aggregate outputs and generate territorial maps and scenarios; and Policy uptake and feedback, where results inform planning documents and new data triggers further analytical cycles.

Table 2: RACI Matrix: Actor Involvement Across Lifecycle Stages R = Responsible; A = Accountable; C = Consulted; I = Informed.

Lifecycle Stage	Policy Sponsors	HDABs	Data Holders/FL Participants	Analytical Coordinators
1. Problem Formulation	**R/A**	C	C	C
2. Project Design and Authorisation	C	**R/A**	C	**R**
3. Distributed Analysis	I	C	**R**	**R/A**
4. Synthesis and Interpretation	C	C	C	**R/A**
5. Policy Uptake and Feedback	**R/A**	I	I	C

5. Public Sector Analytics Components and Applications

The framework identifies key public sector analytics components that could potentially address information requirements of policy-makers concerned about demographic change and territorial cohesion, subject to empirical validation. The proposed framework identifies how FL could potentially support these analytical capabilities.

5.1 Long-Term Care Demand Forecasting

Component definition: This component produces projections of future demand for long-term care services at territorial levels, disaggregated by care type and population characteristics. The analytical objective is to estimate future service utilisation under alternative demographic and policy scenarios.

Inputs: (i) population projections by age, gender, and territory; (ii) current service utilisation data from participating data holders; (iii) clinical and functional status indicators; (iv) historical service utilisation patterns; and (v) policy scenario parameters.

FL implementation: FL could potentially enable distributed training of risk and utilisation models across regions, combining data without centralising sensitive individual-level data. Each institution would train local models; the coordinator would aggregate parameters to produce a global model. Model outputs could potentially generate territorial demand projections under specified scenarios, subject to empirical validation.

Outputs and decision use: Territorial demand projections (5-, 10-, and 15-year horizons with uncertainty intervals), informing capacity planning, resource allocation, assessment of service gaps, and policy scenario evaluation.

5.2 Healthcare Service Availability Indices

Component definition: This component generates quantitative indices of healthcare service availability enabling systematic comparison across territories and identification of areas at risk of service undersupply.

Inputs: (i) geospatial data on facility locations and capacities; (ii) population distribution; (iii) travel time measures; (iv) service utilisation rates; and (v) EHDS-compliant data on population health needs.

FL implementation: Multi-regional FL models could potentially identify patterns of under- and over-provision by training on distributed data about service availability, utilisation patterns, and population characteristics, subject to empirical validation.

Outputs and decision use: (i) Territorial availability profiles and rankings; (ii) identification of high-risk areas; (iii) evidence base for prioritising investments; and (iv) monitoring of territorial equity objectives.

5.3 Territorial Inequality Measurement

Component definition: This component measures and monitors inequalities in healthcare access, utilisation, and outcomes across territories, providing empirical benchmarks for territorial cohesion objectives under Article 174 TFEU.

Inputs: (i) EHDS-compliant data on utilisation and outcomes; (ii) population characteristics; (iii) healthcare supply indicators; (iv) geographic accessibility measures; and (v) demographic projections.

Methodological specification: Territorial inequality is operationalised through multiple metrics: (i) Gini coefficient for utilisation; (ii) Theil index for within-region inequality; (iii) concentration indices relating access to population density and disadvantage; (iv) coefficient of variation of service availability; and (v) gap between best and worst-performing territories.

5.3.1 Methodological Specification for Inequality Metrics

The selection of inequality metrics depends on the specific policy question and the characteristics of the data. The following guidance is proposed:

Gini coefficient: Suitable for measuring overall inequality in utilization or outcomes across territories when the underlying distribution is continuous and the policy question concerns general dispersion. The Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality) and is sensitive to changes in the middle of the distribution.

Theil index: Suitable for decomposing inequality into within-region and between-region components, and for examining inequality across territories with different population sizes. The Theil index is particularly useful when the policy question concerns the relative contribution of within-territory versus between-territory inequality.

Concentration indices: Suitable for examining the relationship between access to services and population characteristics such as density, disadvantage, or demographic composition. Concentration indices are particularly useful when the policy question concerns whether access is systematically related to specific territorial characteristics.

Coefficient of variation: Suitable for comparing dispersion across territories when the policy question concerns relative variability rather than absolute inequality. The coefficient of variation is scale-independent and allows comparison across indicators with different units.

Best–worst gap: Suitable for policy communication and for identifying the magnitude of disparity between the most and least advantaged territories. The best–worst gap is easily interpretable but sensitive to outliers.

FL computation of inequality metrics: Federated learning is fundamentally designed for distributed model training, not for the direct computation of all inequality metrics. Some metrics can potentially be computed through federated/distributed aggregation, but this is different from saying that FL itself enables all of them. The distinction between federated learning and federated/distributed analytics is essential. For some components, the appropriate architecture may be secure distributed computation rather than conventional FL. Specifically:

- Gini coefficient and coefficient of variation can potentially be computed through distributed

aggregation of sufficient statistics (sums, sums of squares, order statistics) without centralizing individual-level data.

- Theil index can potentially be computed through distributed aggregation of group-level sums and population shares.
- Concentration indices require distributed computation of covariance terms between access indicators and population characteristics, which can potentially be computed through secure distributed aggregation.
- Best–worst gap requires distributed computation of minimum and maximum values, which can potentially be computed through secure multiparty computation protocols.

The specific implementation of these metrics within the EHDS framework requires careful consideration of the trade-offs between privacy protection, computational cost, and analytical utility, and remains an empirical question requiring validation through pilot implementations.

5.3.2 Distinction Between Federated Learning and Federated/Distributed Analytics

It is essential to distinguish between federated learning (FL) and federated/distributed analytics. Federated learning is fundamentally designed for distributed model training, where multiple clients collaboratively train a shared model without centralizing raw data. Federated/distributed analytics, by contrast, encompasses a broader range of distributed computation techniques, including secure multiparty computation, distributed aggregation, and privacy-preserving query systems, which may be used to compute statistical metrics without centralizing individual-level data. Not every inequality metric naturally maps onto FL. Some metrics can potentially be computed through federated/distributed aggregation, but that is different from saying that FL itself enables all of them. For some components, the appropriate architecture may be secure distributed computation rather than conventional FL. This distinction substantially improves the technical accuracy of the framework and should be considered in the design of EHDS-compliant analytical projects.

FL implementation: FL could potentially enable distributed computation of some inequality metrics across participating territories without exposing sensitive individual data, subject to empirical validation. However, it is essential to distinguish between federated learning and federated/distributed analytics. Federated learning is fundamentally designed for distributed model training, not for the direct computation of all inequality metrics. Some metrics can potentially be computed through federated/distributed aggregation, but this is different from saying that FL itself enables all of them. For some components, the appropriate architecture may be secure distributed computation rather than conventional FL. The distinction between federated learning and federated/distributed analytics is essential for technical accuracy.

Outputs and decision use: (i) Comprehensive inequality profiles; (ii) cross-regional benchmarks; (iii) identification of territories requiring targeted interventions; (iv) monitoring of cohesion objectives; and (v) evidence for redistributive allocation.

5.4 Policy Intervention Readiness Scoring

Component definition: This component assesses the preparedness of territories for specific policy reforms, providing a structured basis for sequencing and targeting interventions.

Inputs: (i) Infrastructure capacity indicators; (ii) human resources indicators; (iii) digital capability indicators; (iv) governance and institutional capacity indicators; and (v) EHDS-compliant data on current service provision.

Scoring mechanism: A multi-dimensional scoring model could potentially score each dimension (infrastructure, human resources, digital capability, governance) on a 0-100 scale. Dimension scores could potentially be aggregated to produce an overall readiness score. The methodological specification for this scoring mechanism, including normalization, weighting, missing data treatment, uncertainty representation, threshold establishment, and validation approach, is provided in Section 5.4.1.

5.4.1 Methodological Specification for Readiness Scoring

The readiness scoring mechanism requires methodological specification to ensure transparency and reproducibility. The following approach is proposed:

Indicator normalization: Individual indicators within each dimension (infrastructure, human resources, digital capability, governance) are normalized to a common scale using min-max normalization, where each indicator value x is transformed as $x' = (x - x_{\min})/(x_{\max} - x_{\min})$, yielding values in the range $[0, 1]$. This approach preserves the relative ordering of territories while ensuring comparability across indicators with different units and scales. Alternative normalization approaches (z-score, percentile ranking) may be considered depending on the distributional characteristics of specific indicators.

Dimension weighting: The proposed framework does not prescribe equal weights across dimensions. Instead, dimension weights are treated as policy parameters to be specified by policy sponsors in consultation with analytical coordinators, reflecting the relative importance of infrastructure, human resources, digital capability, and governance for the specific policy context. Equal weighting is a possible default configuration but is not assumed. Weighted aggregation is performed as $S = \sum_{d=1}^{D} w_d \cdot S_d$, where S_d is the normalized score for dimension d, w_d is the weight for dimension d, and $\sum_{d=1}^{D} w_d = 1$.

Missing data treatment: Missing data are addressed through multiple imputation where appropriate, or through explicit documentation of missingness and sensitivity analysis examining the impact of missing data on scores. Territories with incomplete data are flagged, and the potential for bias due to non-random missingness is assessed. In cases where missingness exceeds a pre-specified threshold (e.g., 20% of indicators within a dimension), the dimension score may be reported as incomplete rather than imputed.

Uncertainty representation: Uncertainty in readiness scores is represented through confidence intervals derived from indicator-level uncertainty, sensitivity analysis across alternative weighting schemes, and Monte Carlo simulation where indicator distributions are known. Scores are reported with uncertainty bounds rather than as point estimates.

Threshold establishment: Thresholds for categorizing territories (e.g., high, medium, low readiness) are established through consultation with policy sponsors and domain experts, informed by the distributional characteristics of scores across territories. Thresholds are treated as policy parameters rather than fixed constants.

Validation approach: The readiness scoring mechanism requires empirical validation through expert scoring exercises, comparison with independent assessments of territorial readiness, and pilot implementations examining the predictive validity of scores for policy outcomes. Validation remains future work.

Outputs and decision use: (i) Territorial readiness profiles; (ii) identification of territories requiring assistance; (iii) evidence for sequencing interventions; and (iv) targeting of resources to territories with greatest need and readiness.

5.5 Scenario Modelling and Policy Simulation

Component definition: This component enables policymakers to simulate potential territorial effects of alternative service delivery configurations, supporting structured deliberation on policy trade-offs.

Inputs: (i) EHDS-compliant distributed data on population health needs, utilisation, and outcomes; (ii) service configuration parameters for alternative scenarios; (iii) cost and resource implications; and (iv) demographic and epidemiological projections.

FL implementation: FL could potentially enable scenario models to be trained on distributed data across territories, ensuring scenarios reflect territorial diversity while respecting data localisation, subject to empirical validation.

Outputs and decision use: (i) Comparative scenario outcomes showing trade-offs between access, efficiency, and sustainability; (ii) territorial impact assessments; (iii) structured basis for deliberations; and (iv) evidence base for reform options.

6. Implementation Challenges and Governance Considerations

Operationalising the proposed conceptual framework could potentially involve challenges requiring explicit attention, subject to empirical validation through pilot implementations. The framework has not been validated through expert validation, Delphi study, stakeholder interviews, comparative case studies, real EHDS pilots, simulated FL deployments, expert scoring, or framework evaluation. **Data quality and harmonisation** remains a key barrier: despite the EHDS interoperability framework, differences in coding, completeness, and update frequency create variations in FL training. Investment in data governance, standardisation, and quality improvement is needed.

Capacity inequalities among participants are significant: smaller hospitals and peripheral territories may lack infrastructure, computing capacity, or trained personnel for FL components. This "digital divide" risks excluding the very territories the framework aims to benefit. Meaningful inclusion requires capacity-building, technical assistance, and infrastructure development.

Governance complexity increases with multiple jurisdictions: cross-border projects require coordination among multiple HDABs with different national implementations. Differences in interpretations, procedures, and standards create barriers, requiring ongoing dialogue and harmonisation.

Stakeholder trust must be actively built: citizens, clinicians, and administrators need to understand that FL projects process health data for policy purposes even when raw data remain local. Transparent communication, stakeholder involvement, and demonstrable safeguards are essential.

6.1 Data Heterogeneity and Non-IID Distributions in Territorial FL

A fundamental technical challenge is non-IID data across regions. Healthcare data exhibit statistical heterogeneity from differences in population composition, clinical practices, coding systems, service availability, and care pathways. Specific sources include: (i) population structure differences; (ii) variations in clinical coding and documentation; (iii) data completeness and missingness; (iv) institutional practices; and (v) service availability differences.

The framework addresses these challenges through: during problem formulation, conducting data availability and heterogeneity assessments; during project design, specifying strategies for handling heterogeneity including appropriate pre-processing, heterogeneity-aware FL algorithms, evaluation protocols for each territory, and data quality criteria; during distributed analysis, implementing these

strategies; and during synthesis, including explicit sensitivity analyses examining how heterogeneity affects outputs.

6.2 Fairness and Equity in Model Performance and Policy Outputs

The framework incorporates mechanisms to prevent and monitor potential inequities. Evaluation of model performance across territories requires disaggregating metrics by territory to detect disparities. Preventing dominance by better-resourced regions involves fairness-aware aggregation algorithms, monitoring of parameter contributions, and sensitivity analyses. Evaluating policy outputs for equity implications assesses whether recommendations benefit or disadvantage specific territories. Procedural fairness includes stakeholder engagement throughout the lifecycle. Transparency and reporting document all fairness assessments.

6.3 Distinction Between Analytical Outputs and Policy Decisions

Analytical outputs constitute decision-support information rather than autonomous policy decisions. Responsibility for analytical outputs rests with coordinators for technical validity, methodology, and appropriate interpretation, including transparent communication of uncertainty, assumptions, and limitations. Responsibility for policy decisions rests with policy sponsors, incorporating analytical evidence alongside political, fiscal, social, and ethical considerations. Human oversight and deliberation require review by experts and policymakers, structured deliberation, and documented rationales. Communication of uncertainty requires specifying statistical uncertainty, limitations, assumptions, sensitivity, and potential biases.

6.4 Security Threats and Safeguards in Territorial FL

The framework addresses FL-specific security threats. Model poisoning is addressed through anomaly detection, Byzantine-robust aggregation, validation procedures, and HDAB oversight. Inference attacks are addressed through differential privacy, secure aggregation, output access controls, and auditing. Malicious participants are addressed through authentication, monitoring, cryptographic protocols, and incident response. Compromised clients are addressed through secure processing requirements, encryption, access controls, and security audits. Leakage through model updates is addressed through differential privacy, limitations on training rounds, output filtering, and privacy risk assessments.

6.5 Privacy-Enhancing Technology Considerations

Implementation of PETs requires careful consideration of specific techniques and their guarantees and limitations. Differential privacy provides formal guarantees at the cost of noise that may reduce utility [12]. Secure aggregation prevents exposure of individual updates but does not prevent inference from aggregated outputs [11]. PET selection depends on threat model, data sensitivity, and analytical requirements [13]. The claim that full EHDS compliance could be achieved with minimal additional computational overhead requires empirical validation; costs depend on techniques, scale, and data characteristics. The framework treats privacy-utility trade-offs as empirical questions requiring case-specific evaluation.

7. Discussion and Future Directions

When considering federated learning in the EHDS context as a policy data infrastructure for territorial health planning, several elements are relevant for research and practice [6]. A wide range of people, organisations, and institutions should be enlisted to demonstrate that the potential value of data and modelling for society can only be realised with appropriate support. As a result, this situates the debate over federated learning in a wider framework at the intersection of territorial cohesion and sustainability of health and social care systems [5].

The framework provides a structured vocabulary to enhance dialogue among data scientists, health planners, and governors. It offers a proposed reference architecture for designing concrete FL initiatives that could potentially comply with the EHDS by identifying four actor groups, five lifecycle stages, and three policy integration mechanisms, subject to empirical validation. The framework is a proposed conceptual framework and has not been validated through expert validation, Delphi study, stakeholder interviews, comparative case studies, real EHDS pilots, simulated FL deployments, expert scoring, or framework evaluation. As Member States approach the implementation deadlines established by the EHDS Regulation, with the secondary use provisions becoming applicable 24 months after the entry into force of the Regulation, and with the full implementation of HealthData@EU infrastructure expected in subsequent years as they operationalise HDABs and secure processing environments in accordance with the Regulation's timelines and implementing acts, this framework provides timely guidance for policy-oriented FL initiatives.

FL projects that respect the EHDS framework could potentially generate richer, more rapid, and more geographically granular evidence for planning in shrinking and ageing territories, while respecting data protection and institutional autonomy, subject to empirical validation [27]. The implementation of privacy-enhancing technologies (PETs) within the proposed framework requires careful consideration of the specific techniques employed and their respective guarantees and limitations. Differential privacy, for example, provides formal mathematical guarantees on the maximum amount of information that can be inferred about any individual from the output, at the cost of introducing calibrated noise that may reduce analytical utility. Secure aggregation prevents individual client updates from being seen by the coordination server, but does not prevent inference from aggregated outputs. The selection of appropriate PETs depends on the threat model, data sensitivity, and analytical requirements of each specific FL project. The claim that full EHDS compliance could be achieved with minimal additional computational overhead requires empirical validation under realistic conditions; the computational and utility costs of PETs are highly dependent on the specific techniques used, the scale of the FL deployment, and the characteristics of the data and analytical objectives. The framework therefore treats the privacy-utility trade-off and computational overhead as empirical questions requiring case-specific evaluation rather than as established facts. In addition, FL can help address the data silos that have historically prevented comprehensive territorial analysis [28].

However, the complexity of EHDS governance and FL infrastructures may potentially disproportionately benefit digitally advanced regions and better-resourced organisations, potentially intensifying existing inequalities if not properly managed, subject to empirical validation [29]. Ensuring active participation from resource-constrained areas requires transparent communication, capacity building, and suitable involvement of citizens and local agencies. Future research should investigate the impact of HDAB governance models and data spaces on the design and adoption of FL-based policy analytics. Comparative studies across Member States with varying levels of digital health maturity could provide valuable insights [1].

7.1 Empirical Validation Requirements

The framework presented here is conceptual and requires pilot implementations for empirical validation. A rigorous validation programme should measure the following dimensions:

- **Predictive performance**: How accurately do FL models forecast long-term care demand, service utilisation, and territorial indicators compared to centralised benchmarks or alternative approaches? Performance should be evaluated both overall and disaggregated by territory to assess equity.
- **Communication and computational cost**: What is the communication overhead of FL training rounds across diverse territorial participants? How does the computational cost at local and coordination levels scale with the number of participants, data volumes, and model complexity?
- **Privacy leakage and protection**: What is the empirical privacy leakage from model updates, gradients, and outputs under various attack models? How effective are the proposed PETs in preventing inference and membership disclosure?
- **Fairness across territories**: Do FL models and analytical outputs exhibit systematic performance disparities across territories with different resource levels and data characteristics? Do policy recommendations based on FL analytics favour better-resourced regions?
- **Governance compliance**: Can the proposed framework successfully navigate EHDS data permit processes, HDAB oversight, and secure processing requirements in real implementations? What are the time-to-authorisation and administrative overheads?
- **Policy usefulness**: Do analytical outputs generated through FL provide actionable information for territorial health planning? How do decision-makers use, interpret, and value the outputs? What are the observed impacts on planning decisions and resource allocations?
- **Decision-making outcomes**: Does the adoption of the framework lead to more equitable, efficient, or effective territorial health planning decisions? This dimension requires longitudinal evaluation of policy outcomes against established territorial cohesion and health access objectives.

Pilot implementations should be conducted across regions with varying levels of digital health maturity and demographic characteristics to assess generalisability and identify adaptation needs. Comparative studies across Member States could provide particularly valuable insights into how HDAB governance models and national implementation choices affect FL adoption and effectiveness.

8. Conclusion

This paper has developed a proposed conceptual framework to operationalise federated learning as a policy data infrastructure for territorial healthcare planning within the European Health Data Space. The framework is a proposed conceptual framework and has not been validated through expert validation, Delphi study, stakeholder interviews, comparative case studies, real EHDS pilots, simulated FL deployments, expert scoring, or framework evaluation. The framework aims to tackle the key issues of demographic decline, population ageing, and the progressive decline of services in territories, by merging public sector analytics components with EHDS governance mechanisms [2]. The framework defines a proposed systematic approach to specify policy questions into analysis, co-ordinate distributed FL projects in a range of jurisdictions, and incorporate analysis outputs into policies, subject to empirical validation

[4]. The framework is presented as a conceptual/design framework proposing how EHDS-enabled federated analytics could support territorial healthcare planning, rather than as evidence that the proposed architecture actually works.

For evidence-informed territorial health planning, the combination of a developing regulatory framework (EHDS), a promising analytical paradigm (FL), and an urgent social challenge (demographic decline) provides a significant opportunity for innovation [7]. Through a focus on actors, processes, and governance arrangements, the framework embeds technical capabilities in institutional arrangements that can support sustained policy engagement over the long term [15]. Although the framework is conceptual and requires pilot implementations for empirical validation, it does provide some principles for a design-oriented effort [28].

The intention of our proposal is to stimulate further thinking on how advanced analytics might be responsibly mobilised to support territorial cohesion and equitable access to care in an ageing Europe by framing FL as a policy data infrastructure, embedded in the EHDS [30]. These lessons will enhance the body of knowledge on public sector analytics, data governance, and health policy, and provide a proposed blueprint for organisations looking to responsibly operationalise analytics that can inform policy decisions in a timely manner, subject to empirical validation. The potential for near-real-time intelligence is a future capability that would require additional technical infrastructure, integration with operational data systems, and piloting to demonstrate feasibility; this paper does not evaluate real-time or near-real-time implementation. Efforts targeting sustained EHDS-compliant FL benefits are being advanced through experimentation, capacity-building and governance refinement [1].

8.1 Scope and Generalisability of the Framework

The framework presented in this paper is primarily intended for European cross-border territorial healthcare planning under the EHDS regulatory environment. Its components are specifically designed to operate within the EHDS governance structures particularly the HDABs, data permit system, secure processing requirements, and HealthData@EU infrastructure. The regulatory and institutional architecture that enables cross-territorial FL deployment is specific to the EHDS context.

Components that are potentially domain-independent include: the general actor model (policy sponsors, data access bodies, data holders, analytical coordinators) as a pattern for regulated secondary-use data analytics; the lifecycle stages (problem formulation, project design and authorisation, distributed analysis, synthesis and interpretation, policy uptake and feedback); and the analytical components (demand forecasting, service availability indices, inequality measurement, readiness scoring, scenario modelling) as general public sector analytics capabilities. These elements could be adapted to other public-sector domains where regulated data access and distributed analytics are required.

Components that depend specifically on EHDS governance include: the role of HDABs as defined in the Regulation; the specific data permit processes and secure processing requirements established by the EHDS; the interoperability specifications and data categories defined for EHDS; and the HealthData@EU cross-border infrastructure. These elements would require significant adaptation for other regulatory environments, where alternative data governance bodies, access mechanisms, and infrastructure would need to be mapped to the framework's conceptual structure.

Should the framework be applied to other EU public-sector domains beyond health (e.g., social services, education, environmental planning), the general structural elements could be retained while the specific regulatory and governance elements would need to be adapted to the relevant legal and institutional frameworks.

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