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Federated Node (FN): an open-source implementation of the GA4GH task execution service for building federated research networks

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Summary

The Federated Node is an open-source software component for running federated analytics. It is based on existing open standards and is designed to be easy to deploy, manage and integrate with existing infrastructure within data controllers environment for a wide variety of data types and use cases. It has been developed for the PHEMS consortium and is already deployed at multiple partner sites, forming the basis of their federated data sharing network.

Statement of Need

Collaborative biomedical and clinical research increasingly depends on access to diverse, curated real-world data. However, despite progress in open science and digital health infrastructure, such collaboration remains fragmented. Data are often siloed across institutions, jurisdictions, and governance frameworks, particularly in domains such as rare disease and cancer research where sample sizes are inherently small and geographically dispersed. Harmonising and analysing these data collectively are essential for scientific reproducibility and translational impact (Legido-Quigley et al., 2025).

Efforts to promote open and FAIR (Findable, Accessible, Interoperable, Reusable) data practices have revealed the natural tension between data accessibility and usability, and privacy protection. The introduction of robust privacy legislation such as the EU's General Data Protection Regulation (GDPR) and equivalent frameworks worldwide has been vital in safeguarding individual rights. Yet, the resulting regulatory and technical fragmentation has made it increasingly difficult for researchers to move, share, or co-analyse data across national borders e.g. (Mourby et al., 2019). The European Health Data Space (EHDS) and similar policy initiatives recognise that secure federated approaches, where data remain within their source environments but can be analysed collectively, are essential to balance privacy with scientific utility.

Federation has therefore emerged as a practical and ethical mechanism for enabling cross-border research. Rather than copying or aggregating sensitive datasets into central repositories, federated networks allow analytical code to be executed remotely under the control of data custodians, ensuring data never leave institutional boundaries. This paradigm directly addresses legal and ethical constraints on cross-border data movement while maintaining auditability and governance alignment with local policies (Eradat Oskoui et al., 2025). The success of nationwide federated EHR networks in routine emergency-care research (Bienzeisler et al., 2025) demonstrates that such infrastructures are now technically feasible and not merely conceptual.

State of the field

While the technical foundations for federated analytics and learning are in place, translating them into practice remains challenging. Even comprehensive frameworks such as the GA4GH Task Execution Service and the ICODA Common API cannot, by themselves, overcome the deep heterogeneity that exists in real-world healthcare systems. Recent reviews of federated learning in medicine emphasise that most studies still fail to reach clinical utility, citing issues such as non-identical data distributions, methodological bias, heavy communication overheads, and incomplete governance alignment (Joshi et al., 2022; Li et al., 2025). A recent systematic review found that of more than 22,000 papers screened, fewer than 6 per cent involved genuine real-world deployments, underscoring persistent barriers to clinical translation (Teo et al., 2024). Large-scale national programmes such as Australian Genomics further highlight the operational and governance coordination required even before federated analytics are introduced (Stark et al., 2023). These findings collectively illustrate that while federation is technically feasible, its successful implementation demands lightweight, standards-aligned infrastructure that reduces operational friction and lowers the barrier for adoption.

Despite these advances, establishing and maintaining interoperable federated networks remains complex. Implementations often require substantial local customisation to integrate with existing authentication, container orchestration, and registry systems. There is therefore a pressing need for an open, reproducible, and lightweight reference implementation that lowers the barrier for organisations to participate in federated research while adhering to the GA4GH Task Execution Service (TES) specification.

The Federated Node (FN) addresses this need by operationalising the ICODA Common API into a deployable, open-source package built from widely adopted components (Keycloak, nginx, PostgreSQL, Kubernetes). FN allows institutions to host secure, standards-compliant endpoints capable of executing authorised analytical tasks against local datasets, thereby enabling scalable, privacy-preserving, cross-institutional collaboration aligned with international standards.

By operationalizing existing specifications rather than creating proprietary approaches, the FN lowers adoption barriers while ensuring interoperability, as demonstrated by deployment across four European countries with heterogeneous infrastructure as described following.

Research Impact Statement

The FN is deployed in production across multiple sites within the PHEMS (Pediatric Hospitals as European drivers for multi-party computation and synthetic data generation) consortium, enabling the first operational federated analytics network spanning currently four pediatric hospitals across Europe. The PHEMS deployment demonstrates impact, with participating institutions are now actively executing federated queries against real clinical dataset for clinical benchmarking.

The modular design of the FN has enabled integration with existing institutional infrastructure across different technology stacks, demonstrating practical interoperability rather than requiring platform homogeneity.

Software Design

The International Covid-19 Data Alliance (ICODA) developed the Federated Data Sharing Common API or "Common API" as an open standard for a federated data sharing API, as described elsewhere. The Common API is a constrained implementation of the Global Alliance for Genomics and Health Task Execution Service, containing components for meta-data browsing, remote data selection and federated computation.

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The Federated Node (FN) builds upons this open standard, and provides a practical, working implementation of the standard that can be easily deployed and operated into federated research networks. The FN packages an implimention of the Common API with other opensource components including :

- The Common API
- Keycloak
- nginx

The Common API specifies a set of endpoints that provide a framework for organisations that wish to collaborate on federated data sharing and analysis. It provides the structure of the Federated Node API.

Keycloak is used for token and user management, and nginx is used as a reverse proxy, to route incoming requests.

Federated Node deployments are lightweight and use common technologies. Federated Nodes are deployed to a Kubernetes cluster and require a Postgres database for storing user credentials. A deployed Federated Node also needs to be associated with a container registry. This is used to store the remote tasks that are run against the data.

Figure 1 below describes how a federated task is processed when initiated by an authenticated user:

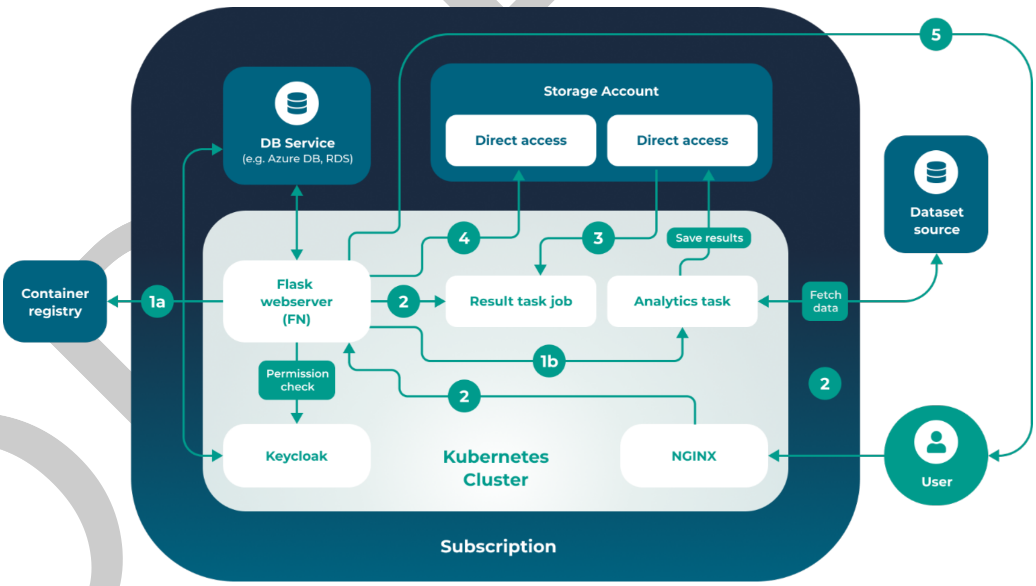

Figure 1: Federated task processing.

- *1a* Before creating the task pod, the FN checks if the docker image needed can be found in the azure container registries associated with the FN.
- *1b* The task pod is created, and the results are saved in the storage account.
- *2* On /results calls, if the task pod is on completed status, a job is created.
- *3* The job's pod will have the 2 storage environments mounted. It fetches the tasks result folder and zips it.
- *4* The webserver reads the zip contents from the live job pod and saves it in its own storage account environment.
- *5* The resulting archive is returned to the end user

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This architecture gives the data owner full control over what code is run against their data, as only scripts stored in the associated container registry can be used, and only authenticated users have the ability to initiate federated tasks.

Extension to support AI

The Federated Node AI is a fork of the main FN project. It introduces an additional endpoint/ask for submitting prompts to a deployed small language model (SLM).

In this configuration instead of retrieving analytical code from an associated container registry the FN is deployed with an LLM or SLM hosted in the same environment as the federated data. Authenticated users can perform federated analysis by sending prompts to the remote SLM, as illustrated following in Figure 2.

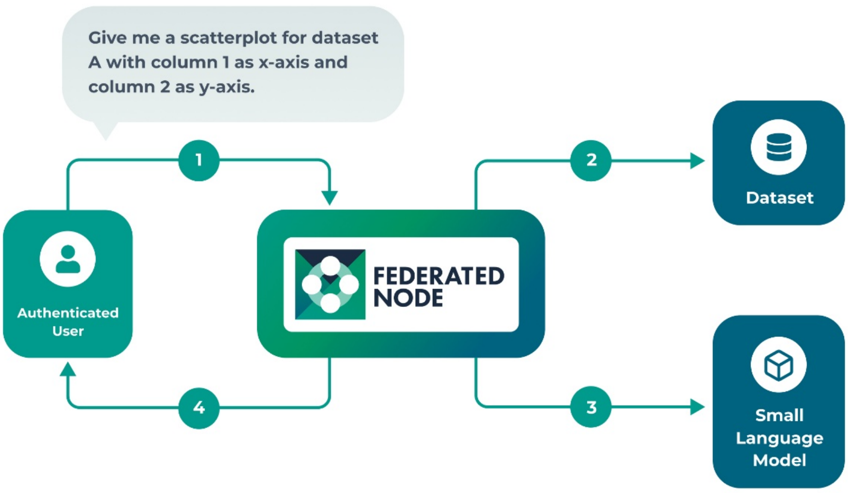

Figure 2: AI Federated task processing.

- *1* User submits prompt e.g. Give me a scatter plot for dataset A, with column 1 as X-axis and column 2 as y-axis
- *2* Federated Node retrieves the data
- *3* Data and prompt are sent to the SLM
- *4* Task is complete and results are returned to the user

By default the FN also retains the last 10 interactions between the users and the SLM providing context when the user wants the SLM to iterate its analysis. Other than these limited additions the FN AI retains the design of the standard Federated Node detailed above.

There are obvious benefits to this approach, primarily that it lowers the barrier to entry for users with limited coding skills. However, we accept that there are a significant issues that need to be resolved before this approach can be considered secure and scalable and that the issues around LLM security and reliability, particularly with regards to mathematical reasoning, are well established. This is not to mention the costs associated with running these models in the data owners infrastructure. Our underlying assumption is that these problems will be resolved by two developments:

1. Smaller, more specialised, and more efficient language models.
2. The emergence of mature workflow patterns, including security and output checks, for the use of language models in data analysis to prevent data exfiltration through prompt engineering.

PHEMS

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Author contributions

R.C. and R.S. designed and developed the software. S.R., R.B. and D.S provided oversight of the project. PHEMS contributed use cases that informed requirements and validation. All authors contributed to the writing and/or review of the manuscript.

AI usage disclosure

All code was written by the development team through conventional software engineering practices. Documentation and this manuscript were authored directly by the listed contributors without AI assistance. Generative AI tools were used as part of the testing and deployment of the AI Federated Task extension.

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References

Bienzeisler, J., Kombeiz, A., Ehrentreich, S., Otto, R., Schirrmeister, W., Pegoraro, M., Brammen, D., Puladi, B., Röhrig, R., & W Majeed, R. (2025). Implementation report on pioneering federated data access for the german national emergency department data registry. *Npj Digital Medicine*, *8*(1). https://doi.org/10.1038/s41746-025-01481-w

Eradat Oskoui, S., Retford, M., Forde, E., Barnes, R., J Hunter, K., Wozencraft, A., Thompson, S., Orton, C., Ford, D., Heys, S., Kennedy, J., McNerney, C., Peng, J., Ghanbariadolat, H., Rees, S., H Mulholland, R., Sheikh, A., Burgner, D., Brockway, M., … Postlethwaite, N. (2025). Developing a prototype for federated analysis to enhance privacy and enable trustworthy access to COVID-19 research data. *International Journal of Medical Informatics*, *195*, 105708. https://doi.org/10.1016/j.ijmedinf.2024.105708

Joshi, M., Pal, A., & Sankarasubbu, M. (2022). Federated learning for healthcare domain - pipeline, applications and challenges. *ACM Transactions on Computing for Healthcare*, *3*(4), 1–36. https://doi.org/10.1145/3533708

Legido-Quigley, C., Wewer Albrechtsen, N. J., Bæk Blond, M., Corrales Compagnucci, M., Ernst, M., Herrgård, M. J., Minssen, T., Ottosson, F., Pociot, F., Rossing, P., & Sulek, K. (2025). Data sharing restrictions are hampering precision health in the european union. *Nature Medicine*, *31*(2), 360–361. https://doi.org/10.1038/s41591-024-03437-1

Li, M., Xu, P., Hu, J., Tang, Z., & Yang, G. (2025). From challenges and pitfalls to recommendations and opportunities: Implementing federated learning in healthcare. *Medical Image Analysis*, *101*, 103497. https://doi.org/10.1016/j.media.2025.103497

Mourby, M., Gowans, H., Aidinlis, S., Smith, H., & Kaye, J. (2019). Governance of academic research data under the GDPR—lessons from the UK. *International Data Privacy Law*, *9*(3), 192–206. https://doi.org/10.1093/idpl/ipz010

Stark, Z., Boughtwood, T., Haas, M., Braithwaite, J., Gaff, C. L., Goranitis, I., Spurdle, A. B., Hansen, D. P., Hofmann, O., Laing, N., Metcalfe, S., Newson, A. J., Scott, H. S., Thorne, N., Ward, R. L., Dinger, M. E., Best, S., Long, J. C., Grimmond, S. M., … North, K. N. (2023). Australian genomics: Outcomes of a 5-year national program to accelerate the integration of genomics in healthcare. *The American Journal of Human Genetics*, *110*(3), 419–426. https://doi.org/10.1016/j.ajhg.2023.01.018

Teo, Z. L., Jin, L., Liu, N., Li, S., Miao, D., Zhang, X., Ng, W. Y., Tan, T. F., Lee, D. M., Chua, K. J., Heng, J., Liu, Y., Goh, R. S. M., & Ting, D. S. W. (2024). Federated machine learning in healthcare: A systematic review on clinical applications and technical architecture. *Cell Reports Medicine*, *5*(2), 101419. https://doi.org/10.1016/j.xcrm.2024.101419