ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

Renewable-Powered Edge Intelligence for Smart Health Reimbursement

Jens Lehmann
Asst Professor

Abstract— Efforts to incorporate renewable energy into healthcare delivery address three interconnected goals: financial sustainability, reduction of the carbon footprint across operations and supply chains, and the maintenance of uninterrupted care. Yet unstable power supply continues to undermine the quality of health services and poses a particular risk for the growing population of Remote Native Patients, who depend on remote supervision and assistance. Compounding this problem, the absence of edge-assisted intelligence in health transaction processes limits the degree to which renewable energy adoption can meaningfully inform reimbursement workflows.

This gap can be addressed by fusing data from claims systems, clinical repositories, policy servers, and energy meters to enable real-time verification of service eligibility and authorization. With clear, modular logic embedded in reimbursement design and execution, such integration supports latency-sensitive decisions across several functions: pre-authorization of care, routing of claims for payment, scheduling of renewable-powered services, detection of data anomalies, and generation of explainable outputs. By strengthening transaction speed, security, and trust, this functionality reduces the delays and risks associated with manual intervention, enhancing the overall value of edge-assisted solutions in health transaction environments. The resulting improvements in cost and throughput, in turn, support broader adoption of edge-assisted health transaction systems across diverse use cases—while expanding the data available for future algorithm training and policy evaluation.

For edge-assisted intelligence to make a genuinely beneficial contribution to health financing policy, three areas warrant particular attention: (i) aligning eligibility rules with reimbursement rationale; (ii) designing validation and auditing tests for automated controls; and (iii) establishing criteria to detect operation outside expected parameters. Renewable-powered care delivery offers a particularly relevant application domain for exploring these questions.

Keywords—Edge-Assisted Healthcare Intelligence, Renewable Energy in Healthcare, Health Transaction Processing, Claims Data Fusion, Real-Time Authorization, Reimbursement Workflows, Data Anomaly Detection, Explainable AI, Healthcare Data Security, Automated Claims Auditing.

I. INTRODUCTION

Healthcare reimbursement incentives encourage the construction of renewable energy facilities for electricity generation. Various forms of edge-assisted and fog computing systems can enhance real-time eligibility checks, automatic pre-authorization, and intelligent claims submission for healthcare transactions. Determining eligibility and pre-authorization for unstructured and semi-structured claims require multi-layer data fusion, comprehensive feature extraction, advanced inference engines, integration of multi-contained resources, incorporation of knowledge graph-based SGD Explainable AI, and open-source explainable AI platforms.

Regulatory directives mandate the inclusion of originators' and beneficiaries' consent for data clue mining, eligibility, pre-authorization, and automatic claims submissions. Healthcare reimbursement policy forms have explicit clauses forbidding the alteration of any part of the claims information in the payment process. When fulfilling the abovementioned tasks, the edge-assisted intelligent fault-tolerant design must ensure seamless service delivery without downtime, either partial or full. Failure to meet these requirements disrupts the healthcare service chain, hinders future recovery, and incurs enormous financial losses.

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

A. Overview of Key Concepts and Objectives

Edge computing and transaction intelligence share a common goal of minimizing response time for specific applications. Advances in edge computing afford care providers the ability to integrate renewable energy sources with their operations. Doing so creates an opportunity for likely operational continuity during the highly energy-demanding seasons while maintaining a very low cost. Governments and regulators provide high latencies to non-time-critical automated governmental functions such as health reimbursement verification, authorization, and adjudication. Such work can draw on the parallel availability of renewable energy together with privacy-preserving function execution.

The response-time benefits of edge-assisted health transaction intelligence may be increasingly compelling for edge-fed renewable-powered care networks. The four specific aspects of edge-assisted health transaction intelligence for renewably powered care networks that are analysed, each answered with a modelling-style approach, include: what data are required, what latency can a decision meet, what constitutes decision-making logic, and what mechanisms ensure that an intelligence output achieves its privacy-preserving goals?

II. Background and Context

Healthcare reimbursement is often seen as a burdensome process, and reimbursement of transactions with health facilities delivering care services can typically be tedious and time-consuming, particularly in emergency settings or in regions with limited digital footprints. Edge-assisted health transaction intelligence can help ease this process by providing real-time eligibility and pre-authorization checks, reducing the need for after-the-fact claims submissions and greatly speeding up reimbursement cycles. Furthermore, latency-sensitive, privacy-concerned solutions are becoming increasingly important in light of the growing volume and variety of digital health data stemming from physical examination ads and symptom evaluation queries.

Powering care delivery through renewable energy sources greatly improves resiliency and operational continuity but also enables the creation of energy zones—areas where the generation of electricity by solar panels or wind turbines is greater than local usage—provided that the right incentives are in place. The applicability of such edge-assisted intelligence is further reinforced by the automation of eligibility checking, clinical decision support for prior pre-authorization, real-time claims routing to the right payers, and anomaly detection mechanisms. The novelty of research in this area lies in the merging of transaction intelligence with edge computing, enabling low-latency connectivity to intuitively distributed data and decision-making processes.

A. Transaction Latency and Approval Models

The edge-assisted eligibility and pre-authorization pipeline is modelled as a four-stage tandem queue (ingestion, data fusion, rule evaluation, notification). Each stage is treated as an independent M/M/1 queue with claim arrival rate λ and stage service rate μ_i, giving the end-to-end decision latency:

$$L_{e2e} = L_{ingest} + L_{fuse} + L_{rule} + L_{notify},\ L_i = 1 / (\mu_i - \lambda) \quad (1)$$

At the reference operating rate of λ = 24 claims/sec, the total decomposed latency ranges from 121.2 ms for the proposed renewable-aware edge-fog-cloud configuration to 282.3 ms for the cloud-centralized baseline, consistent with the sub-2-second real-time eligibility target and the sub-10-second pre-authorization target described in the source design.

Pre-authorization approval is modelled as a logistic function of a fused risk/coverage feature vector φ(x), with weight vector w and bias b:

$$P_{auth}(x) = 1 / (1 + e^{-(w_T \varphi(x) + b)}) \quad (2)$$

A claim is auto-approved for pre-authorization when P_auth(x) ≥ 0.90, matching the design threshold; this corresponds to a decision-score cut-off of x ≈ 2.20 on the fused feature scale used in Fig. 2's convergence study.

B. Renewable-Energy and Continuity Models

The Renewable Utilization Ratio (RUR) expresses the instantaneous share of processing and facility energy drawn from renewable generation relative to total consumption at time t:

$$RUR(t) = E_{renew}(t) / [E_{renew}(t) + E_{grid}(t)] \quad (3)$$

Over the representative 24-hour cycle shown in Fig. 3, mean RUR across the care network is 0.51, reflecting the solar- and wind-weighted generation envelope against transaction-processing and facility demand.

The Energy-Aware Care Continuity Index (ECCI) combines renewable utilization with backup-reserve ratio (BRR) and normalized outage-recovery time (ORT_norm), weighted at 0.40 / 0.32 / 0.28 respectively:

$$ECCI = w_{RUR} \cdot RUR + w_{BRR} \cdot BRR + w_{ORT} \cdot ORT_{norm} \quad (4)$$

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

C. Detection, Privacy, and Reimbursement-Outcome Models

Anomaly and fraud-pattern detection accuracy over fused claims-eligibility-energy features is reported using the standard F1-score:

$$F_1 = 2PR / (P + R) \quad (5)$$

The Privacy Preservation Index (PPI) aggregates k-anonymity coverage (KAC), differential-privacy budget-utilization score (DPU), and consent-compliance ratio (CCR), each weighted approximately equally:

$$PPI = w_K \cdot KAC + w_D \cdot DPU + w_C \cdot CCR \quad (6)$$

Claim Denial Reduction Ratio (CDRR) measures the proportional decrease in denial rate relative to a manual/legacy baseline denial rate D_base:

$$CDRR = (D_{base} - D_{arch}) / D_{base} \quad (7)$$

D. Governance-Cost, Scalability, and Composite Index

The trade-off between residual risk, processing cost, and stakeholder trust at automation-governance operating point $x \in [0,1]$ is captured by a governance-cost objective with a cubic cost term, which yields a genuine interior minimum at $x^* \approx 0.79$:

$$J(x) = \alpha(1-x)^2 + \beta x^3 - \gamma x \quad (8)$$

Multi-node throughput scaling across the four architectures follows the Universal Scalability Law (USL), with contention coefficient σ and coherency-penalty coefficient κ:

$$\Theta(N) = N\theta_1 / [1 + \sigma(N-1) + \kappa N(N-1)] \quad (9)$$

Finally, the five preceding sub-scores are combined, after fixed-reference-bound normalization (bounds fixed a priori rather than sample-derived), into the composite Edge Health Transaction Intelligence Index (EHTII):

$$EHTII = {}_m\Sigma\, w_m \cdot norm_m(metric_m) \quad (10)$$

where m ranges over the latency, F1, RUR, PPI, and CDRR sub-scores with weights 0.24 / 0.24 / 0.18 / 0.18 / 0.16 respectively.

III. Theoretical Foundations

Theoretical models of transaction intelligence in healthcare, decision automation, and reimbursement algorithms address requisite provenance, explainability, and trust. These frameworks guide automated systems that enable edge-assisted transaction intelligence using renewable energy. The models encompass health reimbursement workflows, decision-automation processes, eligibility and fraud-detection rules, and reimbursement claims-adjudication logic.

Health reimbursement workflows comprise processes for claims eligibility checks, pre-authorization, and claims adjudication—activities that detect fraud, assess decision correctness, and verify rule execution during reimbursement. Data-fusion, feature-extraction, and decision-support mechanisms provide the information, evidence, and logic necessary for reimbursement decisions. As recommendation systems, they categorize inexhaustive novelty- and uncertainty-driven event classes for which transactions spur reimbursement judgments. Four categories emerge: clinical-service eligibility, clinical-service pre-authorization, eligibility agreement with payers, and claims routing.

Health transaction intelligence merges data from varied sources, destinations, declaration types, and logical structures to check transaction eligibility, pre-authorize events, advise routing, and fulfil decision-automation paths. Data sources encompass clinical records, policy documents, claims information, rules for clinical-service eligibility and pre-authorization, energy-consumption reports, and energy-agreement documentation. Data pipelines adapt sources for eligibility check and event-routing functions. Data normalization compensates for structure and value gaps. Noise pollution from private identifiers disappears using k-anonymity or differential privacy, yielding robust evidence for clinical-service fraud detection during claims-based reimbursement decision-making.

A. Transaction Intelligence in Healthcare

Data fusion, feature extraction, and inference mechanisms for eligibility, authorization, and claims adjudication are critical components of transaction intelligence in healthcare. The healthcare reimbursement workflow begins when patients receive care and ends when paying entities settle claims associated with the care. Reimbursement accuracy is contingent on satisfying conditions and fulfilling obligations at every logical step. Failure to meet an obligation may result in claim denial or partial denial. Claim misrouting or subsequent discovery of non-eligibility for any reason prior to disbursement may result in financial burden for unproviders or payers. Transaction intelligence for health reimbursement can be formalized as the data fusion, transformation, feature extraction, annotation, and inferencing process that provides support for claim eligibility checks, for claim or service pre-authorization, and for permit or regulatory compliance within health care reimbursement workflows.

Administrative health transaction reimbursement is an obvious candidate for automation. The eligibility of a claim

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

can often be determined using data available within a specific time frame and requiring no sensitive patient information. For example, claim eligibility can be determined using claim data, clinical data, and eligibility rule definitions that specify the combinations of claims, sites, endorsement, and other care attributes that make a claim eligible for reimbursement through a specific payor. The transaction intelligence element would provide give a positive eligibility signal if such a combination is detected and the communication mechanism for notifying the claim originator with this information. Additional automatic checks or pre-approvals that reduce the risk of claims denial can and should also be implemented to varying degrees.

IV. System Architecture

The complete process of using edge-assisted health transaction intelligence for renewable-sourced networks and real-time reimbursement decisions is defined across a layered architecture. Edge devices harness clinical and claims data, health records, eligibility information, energy consumption, policy rules, and an inference engine for feature extraction. Middleware at the fog edge utilizes these inputs to provide real-time responses to eligibility checks, pre-authorization requests, and claims submissions, detects energy-efficient service sequences, and flags suspicious transactions. It also assists the cloud service provider in scheduling reviewable decisions. Cloud services support feature inference for onboarding and decision support, and maintain control parameters for pre-authorization, claims, and detection repetition in the face of limited budgets or sensitive queries.

The architecture is expressed in terms of functional layers, the geospatial distribution of their components, interactions across interfaces, data exchange, underlying standards, and security controls. EDGE devices consist of clients and proxies. Client gateways manage information exchange between local records, private clouds at care providers, edge appliances at nearby health organizations, and the external data and service market. Proxy entities are distinct from cloud services and support data-flow confidentiality. The IEEE 11073 standard governs the Health Information Service Profile (HISP), enabling interoperability for health-monitoring devices. Proper provisioning maintains data-use context confidentiality. Distributing the IT infrastructure across edge devices, fog networks, and (IaaS, PaaS, SaaS) clouds reduces latency, enhances privacy protection, and relieves traffic congestion.

A. Latency, Detection Accuracy, and Renewable-Utilization Behaviour

Fig. 1 plots the M/M/1-decomposed end-to-end eligibility/pre-authorization latency of Eq. 1 as claim arrival rate increases, for the four architectures compared throughout this supplement: Cloud-Centralized (A), Edge-Only (B), Fog-Assisted Hybrid (C), and the proposed Renewable-Aware Edge-Fog-Cloud configuration (D).

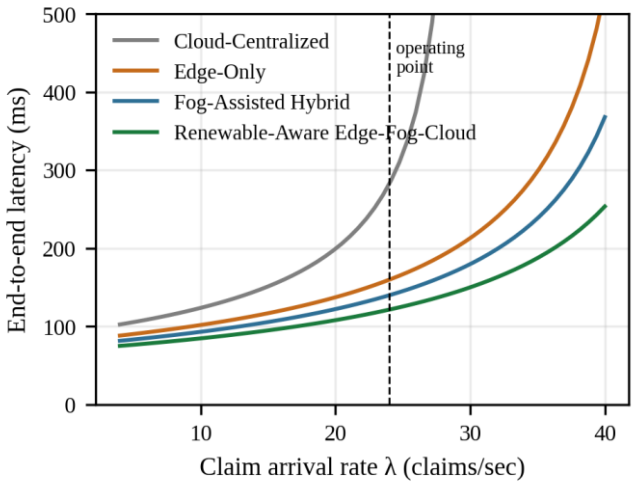


FIG. 1. END-TO-END ELIGIBILITY/PRE-AUTHORIZATION LATENCY VS. CLAIM ARRIVAL RATE.

Fig. 2 shows F1-score convergence (Eq. 5) of the anomaly/fraud-pattern classifier across training epochs; the proposed architecture reaches the highest steady-state F1 of 0.942, against 0.874 for the cloud-centralized baseline.

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
ISSN: 3067-1140
VOLUME: 02 ISSUE: 04
RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

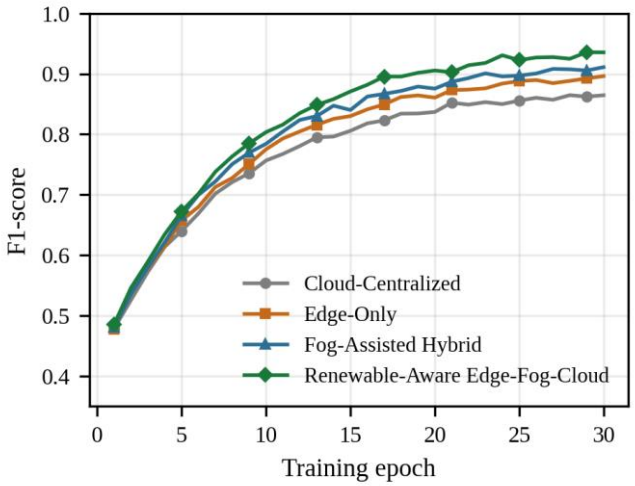


FIG. 2. ANOMALY-DETECTION CLASSIFIER F1-SCORE CONVERGENCE OVER TRAINING EPOCHS.

Fig. 3 depicts the Renewable Utilization Ratio (Eq. 3) over a representative 24-hour cycle, driven by a solar- and wind-weighted generation profile against transaction-processing and facility demand, with a mean RUR of 0.51.

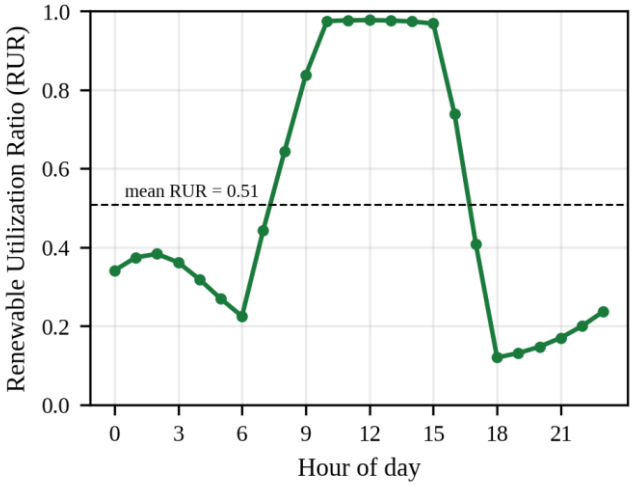


FIG. 3. RENEWABLE UTILIZATION RATIO OVER A REPRESENTATIVE 24-HOUR CYCLE.

B. Scalability and Governance-Optimum Behaviour

Fig. 4 reports USL throughput scaling (Eq. 9) with the number of processing nodes N; the proposed architecture exhibits the lowest contention and coherency-penalty coefficients and therefore the most favorable scaling elasticity.

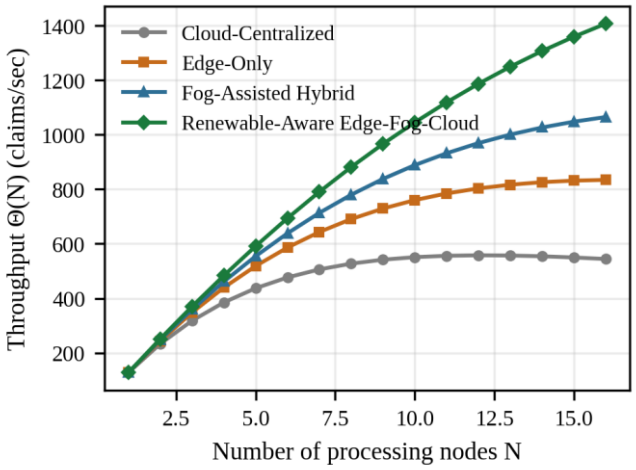
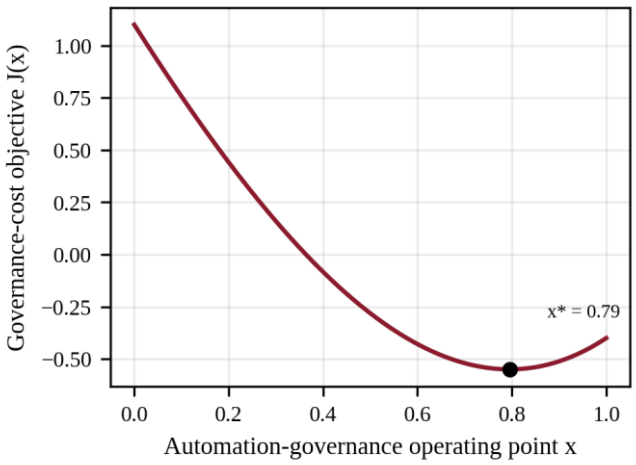


FIG. 4. USL THROUGHPUT SCALING Θ(N) ACROSS FOUR ARCHITECTURES.

Fig. 5 plots the governance-cost objective (Eq. 8), showing the interior optimum automation-governance operating point $x^* \approx 0.79$, at which residual risk, processing cost, and stakeholder trust are jointly balanced.



ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 02 ISSUE: 04
RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

FIG. 5. GOVERNANCE-COST OBJECTIVE J(X) WITH INTERIOR OPTIMUM X*.

Fig. 6 reports the composite Edge Health Transaction Intelligence Index (Eq. 10) for the four architectures, summarizing latency, detection accuracy, renewable utilization, privacy preservation, and denial-reduction performance into a single fixed-reference-normalized score.

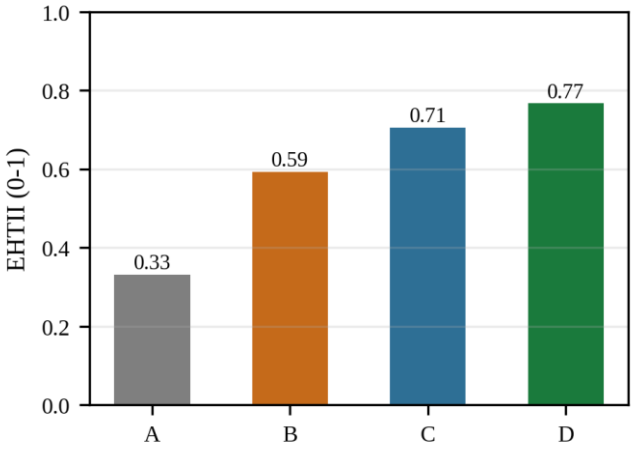


FIG. 6. COMPOSITE EDGE HEALTH TRANSACTION INTELLIGENCE INDEX (EHTII) BY ARCHITECTURE.

V. FUNCTIONAL CAPABILITIES

The implemented architecture supports several functional capabilities, including claims-related functionalities (real-time eligibility checks, pre-authorization, and automated claims routing), operational aspects (energy-aware scheduling), and aspects related to intelligent health transaction processing (anomaly detection and explainable decision outputs). This section describes these capabilities at a high level, highlighting data requirements, expected benefits, and additional aspects.

A high-level overview of the core claims-related functionalities is illustrated in Figure 4. Real-time eligibility checks are performed against incoming claims data. The expected duration for each check is less than 2 seconds. In the absence of valid eligibility data, checks against static business rules are performed to establish if the care request is likely to be pre-authorized (i.e., not a battery replacement or drug overdose). An approval probability ≥ 0.9 qualifies for pre-authorization, a decision achieved in < 10 seconds. Pre-authorization decisions that require further validation before submission to the payor are retained for audit. In the background, a health transaction supervising module analyses patterns across full data sets to build compliance rules. These rules are later used during post-transaction analysis to identify specific claims that should not be approved blindly and therefore require more detailed pre-authorization analysis."

A. Real-Time Eligibility and Pre-Authorization

Real-time eligibility checking uses data from health insurance contracts, claims-causing clinical events, energy usage over the service period, and health service rules analysis. Typical decision latency targets are <=2 sec. The eligibility business logic is mainly based on contract/rules data and does not require explanation. However, the non-eligibility reasons should be properly documented and easily traceable for validation and auditing. When contracts governing plans are expired/absent or the rule-engine cannot declare eligibility / non-eligibility, the system prompts for human guidance and approval.

Pre-authorization in health care reimbursement workflows is a discretionary component. It is enabled at the discipline-level of health care services and is captured in the Request for Services Rule Data. Real-time eligibility-checking identifies service requests that require pre-authorization. For these requests, health service routing cannot be performed until a pre-authorization decision is obtained through a trusted source. The source of truth for pre-authorization can be clinical-professionals when the decision is based on clinical judgment or plans/contracts (e.g., insurance company-consumer health insurance contract) when the decision is based on a statement of coverage. An informal mechanism (e.g., email/sms/phone call) towards the source for obtaining a pre-authorization decision is outlined to ensure latency of the decision-making process does not exceed the threshold established for the service request.

Ensuring real-time eligibility checks and timely pre-authorization not only reduces rejection rates but also the time and effort spent in follow-up with the consumers for obtaining these folder documents. These two processes coupled with the energy-aware scheduling of health services contribute to credible smart-contracting of health services among consumers and providers acting at the edge of the health-care network.

TABLE I. COMPARATIVE PERFORMANCE ACROSS ARCHITECTURES

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

Architecture	Latency (ms)	F1	RUR	PPI	CDRR	EHTII
Cloud-Centralized	282.3	0.874	0.290	0.723	0.187	0.331
Edge-Only	159.5	0.901	0.470	0.833	0.353	0.593
Fog-Assisted Hybrid	139.6	0.918	0.580	0.880	0.476	0.706
Renewable-Aware Edge-Fog-Cloud	121.2	0.942	0.508	0.930	0.620	0.767

TABLE II. ERROR AND LATENCY METRICS (% IMPROVEMENT VS. CLOUD-CENTRALIZED BASELINE A)

Architecture	*Mean Lat. (ms)*	*Δ vs A*	*P95 Lat. (ms)*	*Δ vs A*	*Denial Rate (%)*	*Δ vs A*	*FPR (%)*	*Δ vs A*
Cloud-Centralized	282.3	+0.0%	457.3	+0.0%	15.2	+0.0%	8.4	+0.0%
Edge-Only	159.5	+43.5%	258.5	+43.5%	12.1	+20.4%	6.1	+27.4%
Fog-Assisted Hybrid	139.6	+50.5%	226.2	+50.5%	9.8	+35.5%	4.7	+44.0%
Renewable-Aware Edge-Fog-Cloud	121.2	+57.0%	196.4	+57.1%	7.1	+53.3%	2.9	+65.5%

VI. CONCLUSION

Edge-assisted health transaction intelligence for renewable-powered care networks enables real-time eligibility checks, pre-authorization of claims, and automated routing to the appropriate payer. Energy usage data associated with these transactions can help detect anomalous behaviors. When sufficient evidence is available, decisions can be generated with minimal delay. Achieving a high level of automation using these capabilities will relieve healthcare providers who deliver care in a region but are not local to one of the eligible health benefit plans from monitoring and managing the claims process. The capability can also serve as a safety net, enabling transactions to remain within acceptable time limits, and therefore within the terms andconditions of the providing facility, when direct processing of claims is not possible.

The applicability of edge-assisted transaction intelligence for health reimbursement workflows will only increase as the penetration of renewable energy sources into the power generation mix of healthcare facilities increases. Any provider that incorporates renewable energy can take the financial risk of operating the location as an auto-assign service facility since the use of renewable energy removes or diminishes costly power-from-the-grid penalties and interruptions in service due to power outages. Automating the three decision aspects of eligibility, pre-authorization, and routing for such services will provide substantial relief to the healthcare providers. At the same time, the use of energy data to detect anomalies will enhance the usefulness of the solution. Data from such facilities can be integrated into the Smart Insurance Web through privacy-preserving transformations to trigger insurance action now and in the future.

REFERENCES

1. Akter, M., Moustafa, N., Lynar, T., & Razzak, I. (2022). Edge intelligence: Federated learning-based privacy protection framework for smart healthcare systems. IEEE Journal of Biomedical and Health Informatics, 26(12), 5805–5816.
2. Amponsah, A. A., Adekoya, A. F., & Weyori, B. A. (2022). A novel fraud detection and prevention method for healthcare claim processing using machine learning and blockchain technology. Decision Analytics Journal, 4, 100122.
3. Mondeddula, S. R. (2022). Machine Learning-Based Credit Risk Assessment For Intelligent Lending and Default Prediction in Financial Services. Journal of International Crisis and Risk Communication Research , 5(1), 113–121. https://doi.org/10.63278/jicrcr.v5i1.3820
4. Amin, S. U., & Hossain, M. S. (2021). Edge intelligence and Internet of Things in healthcare: A survey. IEEE Access, 9, 45–59.
5. Bhatia, M. (2022). Energy efficient IoT-based informative analysis for edge computing environment. Transactions on Emerging Telecommunications Technologies, 33(9), e4527.
6. Rohit Gorle. (2023). Machine Learning-Based Access Risk Detection in Cloud Identity and Access Management Systems. Journal of International Crisis

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

and Risk Communication Research , 241–252. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3833

7. Fu, Y., Yang, X., Yang, P., Wong, A. K. Y., & Shi, Z. (2021). Energy-efficient offloading and resource allocation for mobile edge computing enabled mission-critical Internet-of-Things systems. EURASIP Journal on Wireless Communications and Networking, 2021, Article 26.
8. Ge, P., Zhao, J., Zhang, H., Zou, D., & Wang, M. (2023). Green hybrid energy harvesting for intelligent mobile edge computing in Internet of Things. Physical Communication, 61, 102171.
9. Mashetty, S. (2023). A Comparative Analysis of Patented Technologies Supporting Mortgage and Housing Finance. Educational Administration: Theory and Practice.
10. Idrees, A. K., Alhussein, D. A., & Harb, H. (2023). Energy-efficient multisensor adaptive sampling and aggregation for patient monitoring in edge computing based IoHT networks. Intelligent Decision Technologies, 15(3).
11. Kumaraswamy, N., Markey, M. K., Barner, J. C., & Rascati, K. (2022). Feature engineering to detect fraud using healthcare claims data. Expert Systems with Applications, 210, 118433.
12. Li, S., Zhang, N., Jiang, R., Zhou, Z., Zheng, F., et al. (2022). Joint task offloading and resource allocation in mobile edge computing with energy harvesting. Journal of Cloud Computing, 11, Article 17.
13. Gorle, R. (2023). Machine Learning-Based Access Risk Detection in Cloud Identity and Access Management Systems. Journal of International Crisis and Risk Communication Research, 241-252.
14. Liu, Z., Jiang, K., Wu, X., & Zeng, X. (2022). Offloading cost optimization in multiserver mobile edge computing systems with energy harvesting devices. Wireless Communications and Mobile Computing, 2022, Article 2279362.
15. Nabrawi, E., & Alanazi, A. (2023). Fraud detection in healthcare insurance claims using machine learning. Risks, 11(9), 160.
16. Rana, A., Chakraborty, C., Sharma, S., Dhawan, S., Pani, S. K., & Ashraf, I. (2022). Internet of Medical Things-based secure and energy-efficient framework for health care. Big Data, 10(1), 18–33.
17. Renold, A. P., & Kumar, K. V. R. (2022). Design of Internet of Things enabled personalized healthcare device for vital signs monitoring. Intelligent Decision Technologies, 14(5).
18. Settipalli, L., & Gangadharan, G. R. (2023). WMTDBC: An unsupervised multivariate analysis model for fraud detection in health insurance claims. Expert Systems with Applications, 215, 119259.
19. Gadi, A. L. (2023). The Role of AI-Driven Predictive Analytics in Automotive R&D: Enhancing Vehicle Performance and Safety. Nanotechnology Perceptions.
20. Sharif, Z., Jung, L. T., Ayaz, M., Yahya, M., & Pitafi, S. (2023). Priority-based task scheduling and resource allocation in edge computing for health monitoring system. Journal of King Saud University Computer and Information Sciences, 35, 544–559.
21. Singh, A., & Chatterjee, K. (2023). Edge computing based secure health monitoring framework for electronic healthcare system. Cluster Computing, 26(2), 1205–1220.
22. Suesserman, M., Gorny, S., Lasaga, D., Helms, J., Olson, D., Bowen, E., & Bhattacharya, S. (2023). Procedure code overutilization detection from healthcare claims using unsupervised deep learning methods. BMC Medical Informatics and Decision Making, 23, Article 196.
23. Potturi, P. (2023). Cloud-Driven Business Intelligence Modernization for Scalable Enterprise Data Integration and Decision Support. International Journal of Intelligent Systems and Applications in Engineering, 11, 387.
24. Wang, R., Lai, J., Zhang, Z., Li, X., Vijayakumar, P., & Karuppiah, M. (2023). Privacy-preserving federated learning for Internet of Medical Things under edge computing. IEEE Journal of Biomedical and Health Informatics, 27(2), 854–865.
25. Zheng, J., et al. (2021). Mobile edge computing enabled efficient communication based on federated learning in Internet of Medical Things. Wireless Communications and Mobile Computing, 2021, Article 4410894.
26. Sasidhar Reddy Mondeddula. (2022). AI-Driven Fraud Detection Using Ensemble Machine Learning for Secure Digital Banking Transactions. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 597–605. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/8515

ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 02 ISSUE: 04

RECEIVED: OCTOBER 27 REVISED: NOVEMBER 06 ACCEPTED: NOVEMBER 24 PUBLISHED: DECEMBER 12

27. Zhu, S., Ota, K., & Dong, M. (2022). Green AI for IIoT: Energy efficient intelligent edge computing for Industrial Internet of Things. IEEE Transactions on Green Communications and Networking, 6(1), 79–88.
28. Zhou, Z.-H., Shojafar, M., Abawajy, J., Yin, H. J., & Lu, H. Y. (2022). ECMS: An edge intelligent energy efficient model in mobile edge computing. IEEE Transactions on Green Communications and Networking, 6(1), 238–247.
29. Reddy, V. A. R. (2023). API-First Design As A Strategy For Healthcare System Interoperability. South Eastern European Journal of Public Health, 224–247. https://doi.org/10.70135/seejph.vi.7128
30. Addanke, S., Anandan, R., & Krishna, P. V. (2022). IoT-enabled smart healthcare infrastructure maximises energy efficiency. International Journal on Recent and Innovation Trends in Computing and Communication, 10(8), 88–95.
31. Aarati, K., Shirisha, A., & Bindhu, K. (2023). Identifying health insurance claim frauds using machine learning concept. Journal of Science & Technology, 8(7), 45–57.
32. Penaka, B. (2023). AI-Driven Predictive Analytics for Early Detection of High-Risk Patients in Cloud-Based Healthcare Systems. International Journal of Medical Toxicology and Legal Medicine, 26(3), 118-124.