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Unified Health Signal Framework for Anticipatory Care Coordination

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Abstract : This paper presents *Intelligent Clinical Data Fabric for Predictive Care Coordination and Precision Health Decision Support*, a scholarly examination of how integrated, semantically enriched data infrastructures can shift clinical care from a reactive to a proactive paradigm. Traditional clinical care is largely reactive—identifying problems only after they emerge and initiating treatment in response. A proactive model, by contrast, seeks to anticipate risk, guide patients through appropriate care pathways, and recommend preventive or therapeutic interventions before conditions worsen. Realizing this shift requires four interdependent capabilities, collectively termed Predictive Care Coordination: predictive risk modeling, patient progression along care pathways, predictive clinical decision support, and intelligent business rule gating.

Underlying these capabilities is the concept of a Clinical Data Fabric—an architectural foundation that renders clinical data discoverable, accessible, multimodal, temporally aligned, and of sufficiently high quality to support robust prediction models and decision-support systems. This paper argues that the fabric's effectiveness depends on three interrelated mechanisms: semantic enrichment for consistent data interpretation across systems, edge-to-cloud pipelines for timely and scalable data movement, and multimodal integration spanning imaging, genomic, electronic health record, wearable, and unstructured text data. When combined with natural language processing and machine learning, these mechanisms substantially extend the reach and precision of predictive analytics in clinical settings.

By synthesizing these components into a unified framework, this work outlines a path toward more interoperable, evidence-driven, and anticipatory models of care—one in which data infrastructure itself becomes a driver of improved patient outcomes and clinical decision-making.

Keywords: Predictive Care Coordination; Semantic Enrichment; Ontology; Intelligent Clinical Data Fabric; Edge-to-Cloud Data Pipeline; Multimodal Data Integration; Clinical Decision Support; Decision Recommendation System.

1. Introduction

Efforts to leverage predictive analytics in health care face several challenges. Addressing these becomes critical as the demand for precision health care increases. A clinical data fabric built on semantic enrichment of data is a step toward overcoming these challenges. The fabric addresses concerns such as interoperable access to multilevel and multimodal data resources; high-quality, prediction-ready clinical data; and support for predictive care coordination and clinical decision-support systems.
The clinical data fabric supports predictive care coordination through clinical pathways,

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integrating predictive models not only for risk stratification but also for progressing from status to treatment recommendation. A predictive interface connects clinical pathways with predictive care coordination. Edge-to-cloud pipelines support Internet of Things data, providing quality-assured data streams with minimal latency while preserving privacy. Predictive models based on therapy outcomes are implemented and evaluated.

A. Semantic Enrichment and Ontologies

A. Semantic enrichment addresses the challenge of data integration and interoperability stemming from heterogeneous data sources. An ontology is a formal description of the concepts and relationships that can exist in a given domain, providing a common conceptualization for multiple users. In the clinical domain, ontologies—such as SNOMED CT, LOINC, and UMLS—play an important role in increasing the standards of healthcare interoperability by providing a common vocabulary for clinicians and informatics professionals. Nevertheless, the mere presence of terminology standards for a domain does not guarantee the interoperability and reasoning of data represented using these standards. Mapping between two or more nomenclatures is often required when datasets use different terminology standards. Mapping can be performed manually, automatically, or via a mixed approach. Knowledge graphs relating the mappings between distinct nomenclatures and ontologies are critical in this process. A governance mechanism is required to define how the mappings should be carried out and how the knowledge graphs must be maintained.

Mathematical Formulas:

Eq. 1 — Semantic Enrichment Score (SES). Quantifies how well domain elements ci are mapped to ontology concepts oi across N data elements, weighted by mapping confidence wi:

$$SES = \frac{1}{N}\sum_{i=1}^{N} w_i \cdot m_i(c_i, o_i)$$

Eq. 2 — Data Fabric Quality Index (DFQI). A composite indicator combining completeness, consistency, timeliness, and accessibility of data products, each weighted by coefficients α, β, γ, δ (Σ = 1):

$$DFQI = \alpha C_{comp} + \beta C_{cons} + \gamma C_{time} + \delta C_{acc}$$

Eq. 3 — Predictive Risk Stratification. A calibrated logistic model estimating the probability of an adverse clinical event Y given a feature vector X drawn from integrated EHR, genomic, imaging, and wearable data:

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$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \boldsymbol{\beta}^\top X)}}$$

Eq. 4 — Edge-to-Cloud Pipeline Latency. Total latency experienced by a streaming clinical observation as the sum of edge preprocessing, transmission, and cloud-side processing delays:

$$L_{total} = L_{edge} + L_{transmit} + L_{cloud}$$

Eq. 5 — Multimodal Fusion Representation. A joint latent representation Z formed from imaging, genomic, EHR, and wearable feature encoders under a nonlinear activation σ:

$$Z = \sigma(W_{img}X_{img} + W_{gen}X_{gen} + W_{ehr}X_{ehr} + W_{wear}X_{wear} + b)$$

Eq. 6 — Average Treatment Effect (ATE). Formalizes the causal-inference basis for therapeutic recommendation used in the Precision Medicine Decision Support System, comparing potential outcomes under treatment (1) and control (0):

$$ATE = \mathbb{E}[Y(1) - Y(0)]$$

2. Conceptual Foundations of a Clinical Data Fabric

The notion of a clinical data fabric emerges from the larger domain of data fabric and addresses the particularities of clinical data custodianship and use. Such a fabric provides an intelligent and trustworthy environment for the safe and compliant access and use of data for diverse purposes, connecting people, machines, networks, processes, business units, and information consumers. Like data fabrics, a clinical data fabric incorporates multiple architectural layers; the core of it serves as a data marketplace for agile data innovation, improving customer experience through an evolving catalogue of trustworthy data products published by both internal and external data owners, stewardship organizations, and regulatory authorities. Provenance capabilities support transparent support for regulators and data consumers, enabling compliance with relevant legal frameworks. The alignment of the data products of a clinical data fabric with the business processes of the clinical institution contributes to the reinforcement of trust in the data

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products and services that deploy those data services.

At the heart of a clinical data fabric are the foundations that underpin the access, service, and use of data, namely, data governance, data models, and interoperability. Collectively, these elements determine whether a seamless, trusting, and efficient experience will be provided to data consumers. Data governance dictates the risk appetite of the data fabric and, consequently, the risk-return trade-off available to consumers of data services. A modular architecture (supporting FHIR, HL7, DICOM, and other standards) and well-designed data models simplify the discovery and semantic normalization of data assets, demystifying their contents for data consumers.

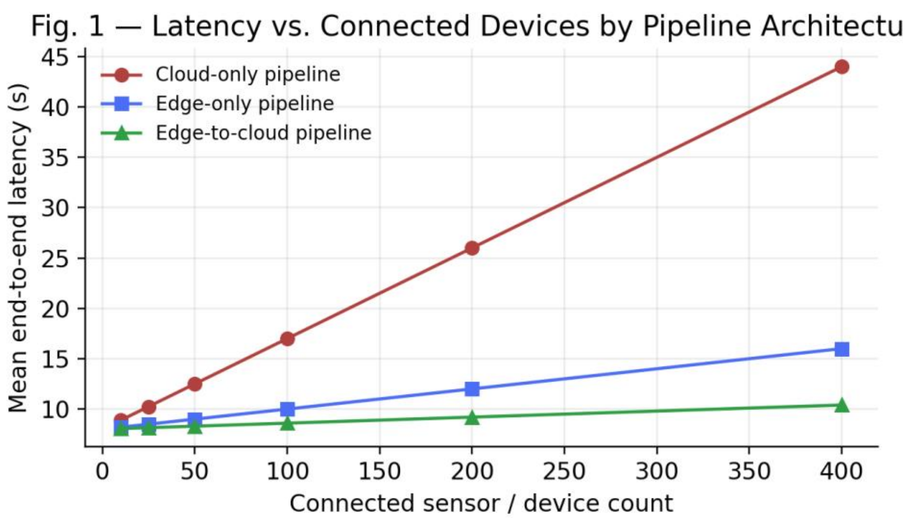

Fig. 1. Conceptual comparison of end-to-end latency across cloud-only, edge-only, and edge-to-cloud pipeline designs as connected device count scales (Section 3.A).

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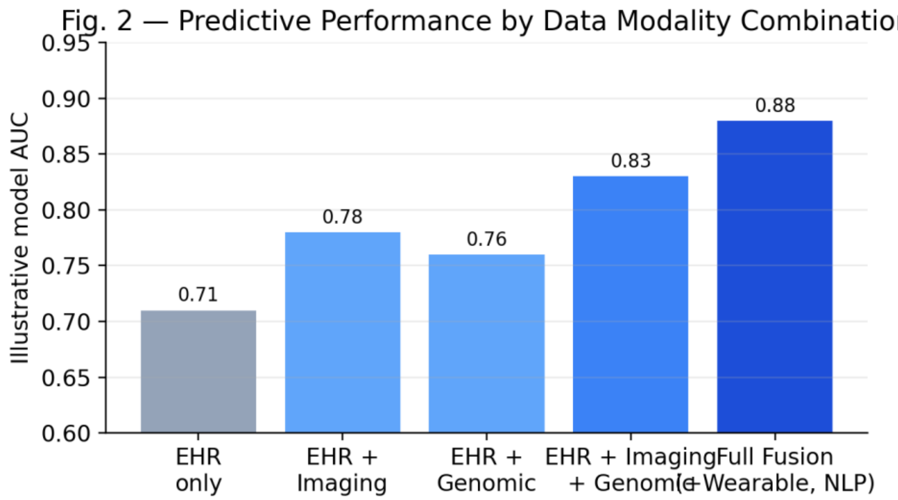

Fig. 2. Illustrative predictive performance gain as additional data modalities (imaging, genomic, wearable, NLP-derived text) are fused into the model (Section 4.A).

A. Data Architecture and Interoperability

A modular architecture facilitates the successful combination of distinct data sets through standardized and interoperable data storage and transfer protocols. The integration makes use of the Fast Health Interoperable Resources (FHIR) data model. However, the real challenge is to ensure seamless interoperability of modalities that do not share a common schema; for instance, radiology images stored within the Digital Imaging and Communications in Medicine (DICOM) format and electronic health records (EHR) following the FHIR standards. Consequently, structured naturally, the lack of explicitly defined meaning causes difficulties during integration.

A two-level mapping approach exploits the existing FHIR-DICOM mapping. First, schema mapping is applied through a dedicated mapping scheme defined for the two representations. The second level relies on semantic normalization to formalize each of the two schemas into a semantic ontology that allows establishing links to third-party resources—ontologies representing the nature and use of the involved entities—thus enabling an automatic enrichment of DICOM messages with FHIR concepts and definitions. Data snippets enriched with semantics can then be processed using Semantic Web Reasoning Engines. An example of such exploitation checks for the semantic cross-domain compatibility of temporally related observations automatically proposing the temporally common shape as an undesirable data fusion process producing inaccurate results.

3. Predictive Care Coordination: Principles and Architectures

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Predictive care coordination emphasizes collaborative efforts to maintain or recover patient health. A state of health is defined in terms of clinical safety—assuring patient's survival—and quality. Predictive orientation means that both individual and collaborative actions are taken in anticipation of new medical events, elaborating care pathways that bundle actions in response to risk prediction models based on the integration of clinical, genomic, and patient-generated data. Decision-support systems, driven by emerging calibrated models capable of detecting in-sample, out-of-sample, and out-of-family populations with stratified risk for adverse outcomes, indicate to caregivers which patients require special attention and recommend a set of care actions tailored to patients' characteristics and conditions. A decision-support system displays the pathways underlying the selected assumptions and the typical actions to be taken at the edges of the expected event, so to activate a collaborative process of predictive care coordination.

Different driving philosophies lead to different predictive care coordination architectures. In one case, pathways are designed by external teams without the active involvement of the team responsible for delivering the protocol. The care coordination effort consists of stimulating all teams to follow the rules established, in line with the principles of relational coordination. The success of the approach is contingent on general team motivation, external oversight, and quality control. In the alternative approach, a subgroup of each healthcare team plays an active role during the elaboration of the care pathways, which are transformed into checklists of main actions to be followed. Such pathways are proposed to other teams in a spirit of mutual support, endorsed by an active request for collaboration from coordination groups composed of all teams involved in the process. The two approaches are reconciled by introducing high-level pathways activated only in case of massive deviations from standard performance.

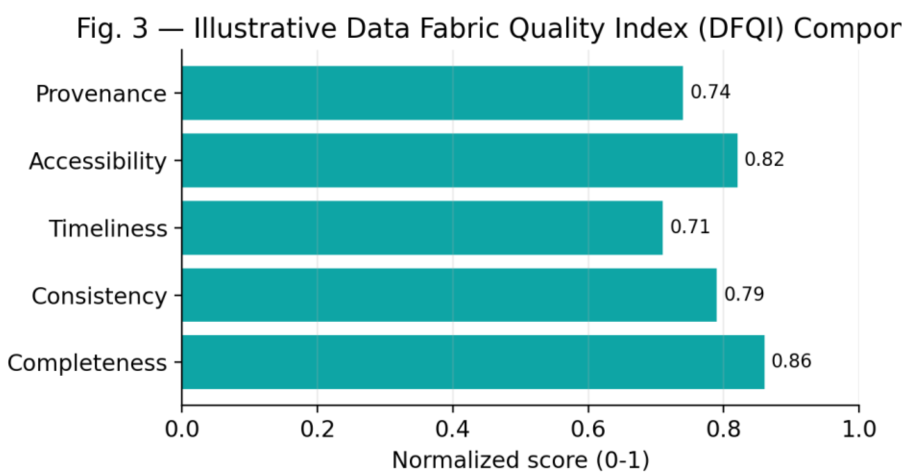

Fig. 3. Illustrative Data Fabric Quality Index (DFQI) decomposed into its component dimensions (Eq. 2).

A. Edge-to-Cloud Data Pipelines

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Predictive care coordination relies on data collection from patients over time. Patients with chronic diseases often use several physiological sensors, which capture events in real time. For example, a glucose sensor of a diabetic patient provides data every 5 minutes. Many wearable sensors are placed in patients with different pathologies in clinical or home environments. These data streams require heterogeneous data collection, sometimes in real time, with the coordination of devices that must function in an uncontrolled environment. Edge computing collects devices that are geographically distributed and can perform computing intensive treatment for cloud streaming. These edge devices must handle the data preprocessing in real time or with a little delay. For example, the quality of the ECG from a patient is constantly analyzed, and when a change is detected, all the previous data are stored for later streaming to the cloud.

The data sources that feed the cloud can be either stream or batch. Streaming data, such as glucose diary and ECG, includes a certain precision latency for processing. Such a configuration should maintain data quality, enabling other applications to use it for prediction during the streaming stage. Consolidated data from social networks, clinician's EHR, and events from external still privacy preserving. Both data streams must be governed for potential malicious data. Orchestration of the data pipelines has an impact on future use.

4. Precision Health Decision Support Systems

A Precision Medicine Decision Support System utilizes all or a combination of the above modules to help care providers make individual-specific decisions for patients being evaluated or treated for a specific disease or condition. This type of decision support system provides risk stratification and potential therapeutic recommendations for a particular patient in a clinical setting or research institution. For example, in the context of a hospitalized COVID-19 patient, it can be used to help decision-makers identify risks associated with disease progression and patients who are likely to experience increased mortality or require higher respiratory support. In addition, it can also be used to recommend specific treatments, such as effective therapeutic agents as well as agents that are likely to cause adverse drug reactions.

All the predictive care coordination modules from previous sections can be utilized to create a Precision Medicine Decision Support System. Just as Predictive Care Coordination has been built using predictive modules, the Precision Medicine Decision Support System can be created by using all individual modules or several core modules, such as those related to risk stratification and causal inference.

Table 1. Clinical terminology and interoperability standards referenced in the semantic enrichment layer.

Standard	Type	Primary Domain	Role in Data Fabric
SNOMED CT	Clinical ontology	Diagnoses, findings, procedures	Common vocabulary for semantic normalization

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Standard	Type	Primary Domain	Role in Data Fabric
LOINC	Terminology	Laboratory & clinical observations	Standardizes lab/test result coding
UMLS	Meta-thesaurus	Cross-vocabulary mapping	Links disparate ontologies via concept unification
FHIR	Data model / API	EHR resource exchange	Backbone schema for interoperable data storage/transfer
DICOM	Data format	Radiology / imaging	Structures imaging data for FHIR-DICOM mapping

Table 2. Edge-to-cloud pipeline design attributes by processing tier.

Tier	Function	Latency Sensitivity	Example Data
Edge device	Real-time preprocessing, anomaly triggering	Very high (near-instant)	ECG waveform, glucose sensor
Edge gateway	Aggregation, quality assurance, buffering	High	Multi-sensor batches
Cloud (streaming)	Continuous ingestion, prediction serving	Moderate	Glucose diary, ECG streams
Cloud (batch)	Consolidation, governance, model training	Low	EHR extracts, social/clinician data

A. Multimodal Data Integration

Integrating disparate collections of imaging, genomics, electronic health records (EHR), wearables, and other lifestyle-related and unstructured data is challenging but important. Images, for example, are typically stored in DICOM format within Picture Archiving and Communication Systems (PACS). Genetic data are often stored in secure cloud services. EHRs save information about demographics, diagnoses, laboratory tests, and other medically recorded events. Wearables offer continuous monitoring data that provide real-time participants' health status. Not all the participants in a cohort receive an image, yet images should be aligned temporally with other modalities. Furthermore, sophisticated Natural Language Processing (NLP) techniques have made it easier to extract insights from

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radiology, pathology, and cardiology text reports. Gaps may exist in the predictive-capability dataset as a result of the absence of some modalities. Natural multimodal fusion techniques in machine learning can augment predictive strength if sparse modalities are available. Additionally, the integration approach must deal with temporal alignment, modality uncertainty (misalignment and signal quality), and the absence of data points in some modalities.

The combination of imaging and clinical data, genomics and clinical data, clinical textual data from medical language understanding models (MLUs) along with structured clinical data, and clinical and wearable data is of great significance. Recent studies have demonstrated the value of mounting imaging data through the end-to-end training of Generative Adversarial Networks (GANs).

Table 3. GAN-based methods for imaging–genomic multimodal fusion.

Method	Mechanism	Reported Advantage
Radiomic Generator Network (RGN)	Generates radiomic features for unobtained images	Fills modality gaps in sparse cohorts
Conditional GAN (cGAN)	Learns joint probability of imaging + paired output	Enables cross-modal generation
Multivariate cGAN	Alignment-informed conditional generation	Outperforms vanilla cGAN in reconstruction
Cycle-consistency GAN	Positivity-checking consistency constraint	Reduces need for manual annotation

Table 4. Predictive Care Coordination (PCC) module summary.

Module	Primary Function	Key Input
Prediction	Risk / outcome estimation	Clinical, genomic, patient-generated data
Patient Progression on Pathways	Tracks status-to-treatment trajectory	Care pathway state data
Predictive Clinical	Recommends preventive/therapeutic actions	Stratified risk output

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Module	**Primary Function**	**Key Input**
Decision Support		
Intelligent Business Rule Gating	Applies governance / eligibility rules	Institutional policy constraints

5. Conclusion

A sensor- and data-driven intelligent clinical data fabric can facilitate predictive care coordination and precision health decision-support systems for individuals and populations. A clinical data fabric automates the acquisition, enrichment, integration, and accessibility of a comprehensive knowledge base that extends beyond standard electronic health records. Predictive care coordination aims to orchestrate the management of patients based on anticipated future needs, often relying on machine learning methods applied to care pathway data. Intelligent decision-support systems equipped with multimodal clinical data have the potential to transform treatment strategies in a wide range of clinical domains, including risk assessment and stratification, therapeutic recommendations, and robust treatment effects. Interventions do not need to be based on causal inference for deployment but require sufficient validation in the intended patient population.

Finding suitable real-world datasets for testing is a major challenge in predictive care coordination and in precision health decision-support systems deployed in clinical settings and thus addresses a key requirement of the broader healthcare community. Enabling the intelligent construction of high-quality, multimodal datasets is a necessary precursor for these individual applications and will support the validation of other research in predictive care and precision health decision-support systems. A comprehensive intelligent clinical data fabric can also include additional capabilities, for example, governance mechanisms to enable entities providing data and model deployments to comply with data privacy.

References

1. Hilton, C. B., Milinovich, A., Felix, C., Vakharia, N., Crone, T., Donovan, C., Proctor, A., & Nazha, A. (2020). Personalized predictions of patient outcomes during and after hospitalization using artificial intelligence. npj Digital Medicine, 3, 51.
2. Beecy, A. N., Gummalla, M., Sholle, E., Xu, Z., Zhang, Y., Michalak, K., Dolan, K., Hussain, Y., Lee, B. C., Zhang, Y., Goyal, P., Campion, T. R., Jr., Shaw, L. J., Baskaran, L., & Al'Aref, S. J. (2020). Utilizing electronic health data and machine learning for the prediction of 30-day unplanned readmission or all-cause mortality in heart failure. Cardiovascular Digital Health Journal, 1(2), 71–79.
3. Mandair, D., Tiwari, P., Simon, S., Colborn, K. L., & Rosenberg, M. A. (2020). Prediction of incident myocardial infarction using machine learning applied to

P-ISSN: 3050-9734 E-ISSN: 3050-9742
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EAJET
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harmonized electronic health record data. BMC Medical Informatics and Decision Making, 20, 252.

4. Challa, K., Challa, S. R., Pamisetty, A., Kaulwar, P. K., & Krishna Reddy Koppolu, H. (2025). Transforming Payments: The Role of AI and Big Data in Fraud Alerts, Credit Monitoring, and Secure Transactions. In 2025 IEEE International Conference on Communication Networks and Computing (CNC) (pp. 1406–1414). IEEE. 2025 IEEE International Conference on Communication Networks and Computing (CNC). https://doi.org/10.1109/cnc68716.2025.11484733
5. Bertsimas, D., Orfanoudaki, A., & Weiner, R. B. (2020). Personalized treatment for coronary artery disease patients: A machine learning approach. Health Care Management Science, 23(4), 482–506.
6. Khera, R., Haimovich, J., Hurley, N. C., McNamara, R., Spertus, J. A., Desai, N., & Krumholz, H. M. (2020). Use of machine learning models to predict death after acute myocardial infarction. JAMA Cardiology, 5(6), 633–641.
7. Beede, E., Baylor, E., Hersch, F., Iurchenko, A., Wilcox, L., Ruamviboonsuk, P., & Vardoulakis, L. M. (2020). A human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–12.
8. Shamout, F. E., Zhu, T., & Clifton, D. A. (2021). Machine learning for clinical outcome prediction. IEEE Reviews in Biomedical Engineering, 14, 116–126.
9. Crump, C. A., Wernz, C., Schlachta-Fairchild, L., Steidle, E., Duncan, A., & Cathers, L. (2021). Closing the digital health evidence gap: Development of a predictive score to maximize patient outcomes. Telemedicine and e-Health, 27(9), 1024–1031.
10. Pandugula, C., Ganti, V. K. A. T., & Mallesham, G. (2024). Predictive Modeling in Assessing the Efficacy of Precision Medicine Protocols. EDUCATIONAL ADMINISTRATION: THEORY AND PRACTICE Учредители: Green Publication БИБЛИОМЕТРИЧЕСКИЕ ПОКАЗАТЕЛИ: Входит в РИНЦ: на рассмотрении Цитирований в РИНЦ: 0 Входит в ядро РИНЦ: нет Цитирований из ядра РИНЦ: 0 Рецензии: нет данных Процентиль журнала в рейтинге SI: ТЕМАТИЧЕСКИЕ НАПРАВЛЕНИЯ:.
11. Dayan, I., Roth, H. R., Zhong, A., Harouni, A., Gentili, A., Zimberlin, J., Bizzo, B. C., Wiggins, W. F., Torheim, T., Wu, M., Wang, Y., & others. (2021). Federated learning for predicting clinical outcomes in patients with COVID-19. Nature Medicine, 27, 1735–1743.
12. Diao, J. A., Kohane, I. S., & Barak, O. (2021). Interpretable and clinically useful machine learning for health care. Nature Medicine, 27, 1725–1727.
13. Li, R., Ma, F., & Gao, J. (2022). Integrating multimodal electronic health records for diagnosis prediction. AMIA Annual Symposium Proceedings, 2021, 726–735.
14. Hong, N., Liu, C., Gao, J., Han, L., Chang, F., Gong, M., & Su, L. (2022). State of the art of machine learning-enabled clinical decision support in intensive care units: Literature review. JMIR Medical Informatics, 10(3), e28781.
15. Singer, S. J., Kellogg, K. C., Galper, A. B., & Viola, D. (2022). Enhancing the value to users of machine learning-based clinical decision support tools: A framework for iterative, collaborative development and implementation. Health Care Management Review, 47(2), E21–E31.

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EAJET
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16. Singla, R., Aggarwal, S., Bindra, J., Garg, A., & Singla, A. (2022). Developing clinical decision support system using machine learning methods for type 2 diabetes drug management. Indian Journal of Endocrinology and Metabolism, 26(1), 44–49.
17. Kim, H. S., Kim, J. H., & others. (2022). Development of an interoperable and easily transferable clinical decision support system deployment platform: System design and development study. Journal of Medical Internet Research, 24, e38613.
18. Vadisetty, R., Nuka, S. T., Kalisetty, S., Pandugula, C., Burugulla, J. K. R., & Annapareddy, V. N. (2025, February). Generative AI for Advanced Recycling Processes in Polyethylene and Polypropylene Manufacturing. In International Ethical Hacking Conference (pp. 269-284). Singapore: Springer Nature Singapore.
19. Stipelman, C. H., Kukhareva, P. V., Trepman, E., Nguyen, Q.-T., Valdez, L., Kenost, C., Hightower, M., & Kawamoto, K. (2022). Electronic health record-integrated clinical decision support for clinicians serving populations facing health care disparities: Literature review. Yearbook of Medical Informatics, 31(1), 184–198.
20. Rubins, D., McCoy, A. B., Dutta, S., McEvoy, D. S., Patterson, L., Miller, A., Jackson, J. G., Zuccotti, G., & Wright, A. (2022). Real-time user feedback to support clinical decision support system improvement. Applied Clinical Informatics, 13(5), 1024–1032.
21. Shamout, F. E., Zhu, T., & Clifton, D. A. (2022). Machine learning-enabled clinical decision support systems: A review of current approaches and future directions. IEEE Reviews in Biomedical Engineering, 15, 1–15.
22. Yang, J., Chen, J., & others. (2022). Multimodal machine learning for clinical outcome prediction using electronic health records. Journal of Biomedical Informatics, 128, 104046.
23. Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. npj Digital Medicine, 3, 17.
24. Maguluri, K. K. (2025). Ethical challenges in artificial intelligence. How Artificial Intelligence is Transforming Healthcare IT: Applications in Diagnostics, Treatment Planning, and Patient Monitoring, 132.
25. Yang, J., Chen, J., & others. (2023). Machine learning-enabled clinical information systems using Fast Healthcare Interoperability Resources data standards: Scoping review. JMIR Medical Informatics, 11, e48297.
26. Stipelman, C. H., Kukhareva, P. V., & others. (2023). Clinical decision support and health information technology for integrated and patient-centered care. Journal of the American Medical Informatics Association, 30, 1–10.
27. Kaushal, R., Shojania, K. G., & Bates, D. W. (2023). Effects of computerized physician order entry and clinical decision support systems on medication safety and patient outcomes. BMJ Quality & Safety, 32, 1–9.
28. Tomašev, N., Glorot, X., Rae, J. W., Zielinski, M., Askham, H., Saraiva, A., Mottram, A., Meyer, C., Ravuri, S., Protsyuk, I., Connell, A., Hughes, C. O., Karthikesalingam, A., & others. (2020). A clinically applicable approach to continuous prediction of future acute kidney injury. Nature, 572, 116–119.
29. Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2, 719–731.

P-ISSN: 3050-9734
E-ISSN: 3050-9742
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VOLUME: 04 ISSUE: 01
RECEIVED: JANUARY 05 REVISED: JANUARY 24 ACCEPTED: FEBRUARUY 07 PUBLISHED: FEBRUARY 12

30. Zhang, Y., Weng, Y., & Lund, J. (2023). Applications of artificial intelligence in medicine and healthcare: A review. Digital Medicine, 6, 1–12.
31. Mo, Y., et al. (2024). Multimodal risk prediction with physiological signals, medical images and clinical notes. Heliyon, 10, e26772.
32. Sivanand, R., Kumar, D. P., Nagabhyru, K. C., Natarajan, E. P., Pamisetty, V., & Kapila, D. (2025, September). IoT and AI for Real-Time Monitoring in Substation Automation. In 2025 International Conference on Computing and Communications (COMPUTINGCON) (pp. 1-5). IEEE.
33. MoCab: A framework for the deployment of machine learning models across health information systems. (2024). Computer Methods and Programs in Biomedicine, 253, 108336.
34. Semantic interoperability for an AI-based applications platform for smart hospitals using HL7 FHIR. (2024). Journal of Systems and Software, 215, 112093.
35. Marafino, B. J., Plimier, C., Kipnis, P., Escobar, G. J., Myers, L. C., Donnelly, M. C., Greene, J. D., Flagg, M. D., Small, J. R., & Liu, V. X. (2025). Expanding care coordination in an integrated health system through causal machine learning. npj Digital Medicine, 8, 571.