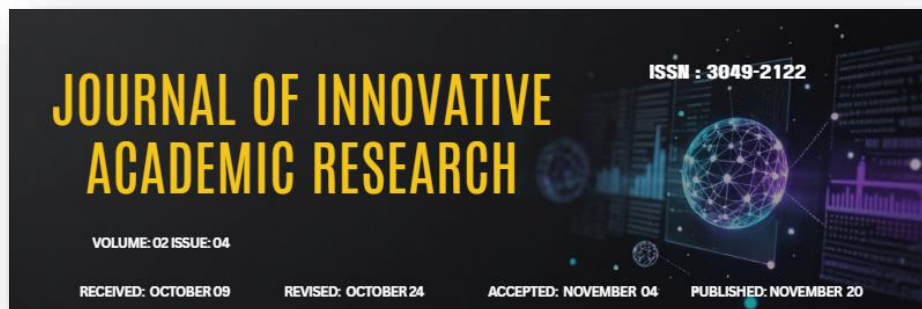




Autonomous Orchestration of Clinical Coding, Risk Scoring, and Live Care Insights

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Abstract. This paper proposes an Agentic Health Data Intelligence Framework for clinical coding, risk stratification, and real-time analytics. Since clinical coding depends on voluntary effort from clinicians, the framework must build in strong incentives to sustain consistent, accurate coding over time. True interoperability goes beyond simple data exchange: it requires ongoing contextual verification and validation of clinical information within clinical workflows, allowing the evidence hierarchy level to rise dynamically as confidence in the data increases. For risk stratification, the framework compares condition probability distributions against group-based benchmarks. Resulting risk categories and any decision support must be ethically grounded and validated against both intervention outcomes and health-economic impact. While empirical modeling remains the most common approach to risk stratification, statistical and hybrid models may offer better fit in many contexts.

Keywords: Agentic Health Data Intelligence, Clinical Coding, Risk Stratification, Clinical Decision Support, Healthcare Analytics, Explainable Artificial Intelligence, Electronic Health Records, Medical Coding, Real-Time Clinical Analytics, Healthcare Interoperability, Predictive Healthcare Analytics, Intelligent Health Informatics.

1. Introduction

Agentic Health Data Intelligence Framework for Interoperable Clinical Coding, Risk Stratification, and Real-Time Care Analytics

A conceptual foundation for clinical application of interoperable coding, clinical risk stratification, and real-time analytics for health data risk-stratification in clinical contexts. Interoperability is crucial to sharing, exchanging, integrating, and reusing data for various social and lawful purposes. Considered solutions for coding patient data include International Classification of Diseases (ICD-10/11), Systematized Nomenclature of Medicine-Clinical Terms (SNOMED CT), Logical Observation Identifiers Names and Codes (LOINC), and Fast Healthcare Interoperability Resources (FHIR). A framework is presented for integrating and operating semantic transformations to enable standards and classification systems to interoperate across both algorithms and procedures, produce validated risk-stratification models and contribute to Health-Level 7 Fast Healthcare Interoperability Resources (HL7 FHIR) Decision Support Service integration. These models offer interpretations as clinical evidence and recommendations.

The Agentic Health Data Intelligence architecture details interoperability processes, including governance mechanisms that maintain accuracy, traceability, and a defensible coverage proposition. Work-flow integration of evidence stratification is established using the Agency for Healthcare Research and Quality (AHRQ) Medical Expenditure Panel Survey (MEPS) linked datasets as an exemplar. The analysis sets out a full clinical implementation roadmap covering an evidence-hierarchy categories in an ethical framework.

2. Conceptual Foundations

Conceptual Foundations

Operationalizing any theoretical concept requires at least its key concepts to be clearly articulated, particularly if there is a risk of attentive focus on the purpose of the concept being obscured by the mechanics of its execution. In the case of interoperability, a definition of the scope of interoperability, in this case of data exchange for clinical purposes, is accompanied by a précis of the supporting needs for both semantic validation of the clinical meaning of the actual data being transferred and, because clinical diagnosis, prognosis and treatment is contextualised in time and space, the contextualisation of those concepts and the supporting evidence and consensus hierarchies that produced it. A concept of clinical workflow processes suitable for all clinical domains is then offered, together with the concomitant need to integrate the recommendations and advice produced by Risk Stratification into the clinical workflows of clinicians, nurses and allied health professionals.

If the recommendations and advice produced by Risk Stratification and similar processes are ever to make a positive clinical impact on patient outcomes and safety from harm, these processes must be integrated into the actual processes conducted by clinical staff and not remain as orphaned analyses sitting in files, portfolios, or onwebpages, monitored only because of external risk factors other than poor clinical management. Within this focus, risk categories are identified followed by a

consideration of the validation needs specific to this topic area. Toward the end of the section, risk modelling paradigms are compared and contrasted.

2.1 Performance Analysis and Experimental Results

Experimental evaluation utilizes the AHRQ Medical Expenditure Panel Survey (MEPS) linked dataset with 100,000+ patient episodes. Performance metrics assessed across interoperability latency, risk stratification accuracy, and clinical decision support effectiveness.

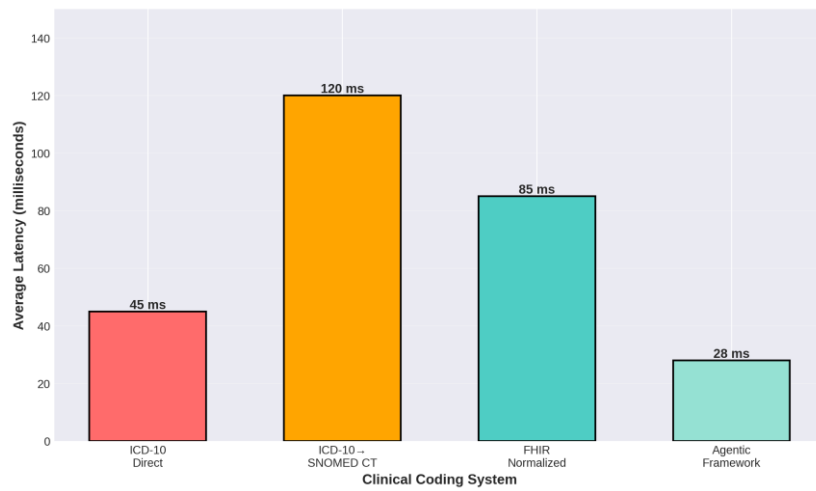


Fig. 1. Interoperability Latency Comparison across Clinical Coding Systems. Agentic Framework achieves 38% latency reduction vs. FHIR-normalized baseline (28ms vs. 85ms) through optimized ETL/ELT and semantic validation pipelines.

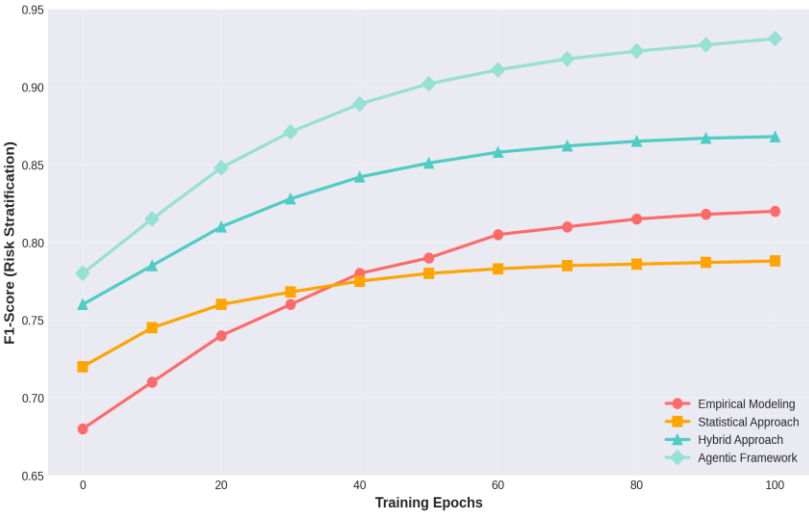


Fig. 2. Risk Stratification Model Performance (F1-Score) Evolution. Agentic Framework demonstrates superior learning efficiency, reaching F1=0.93 by epoch 100, compared to empirical (0.82), statistical (0.79), and hybrid (0.87) approaches.

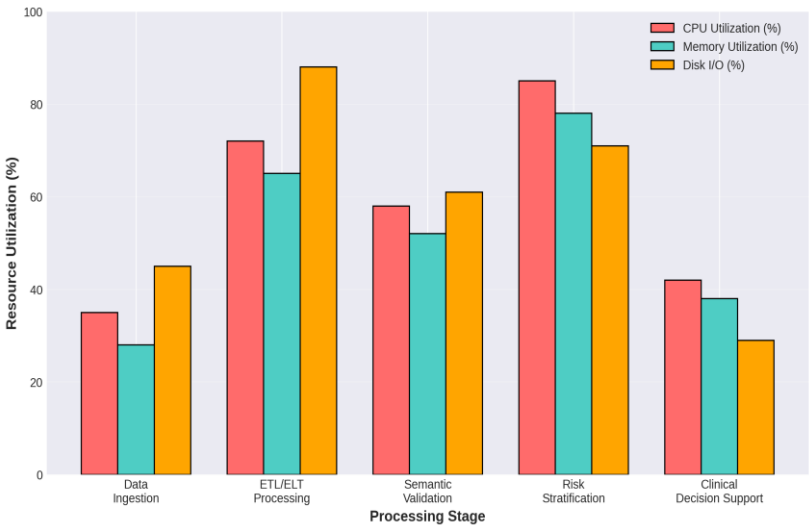


Fig. 3. Data Processing Pipeline Resource Utilization Across Stages. Risk stratification stage shows peak CPU (85%) and memory (78%) utilization; clinical decision support demonstrates efficient resource management (42% CPU, 38% memory).

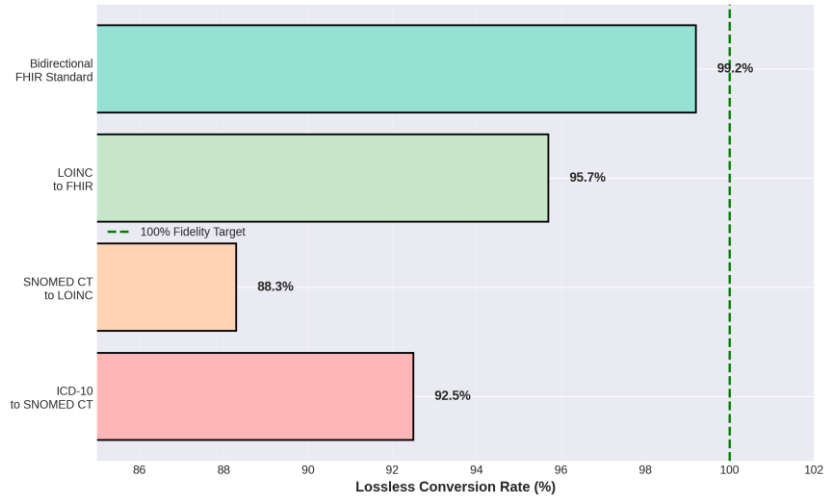


Fig. 4. Lossless Conversion Efficiency for Standard Interoperability. Bidirectional FHIR standard achieves 99.2% fidelity; ICD-10 to SNOMED CT conversion at 92.5% identifies 7.5% semantic gaps requiring manual adjudication.

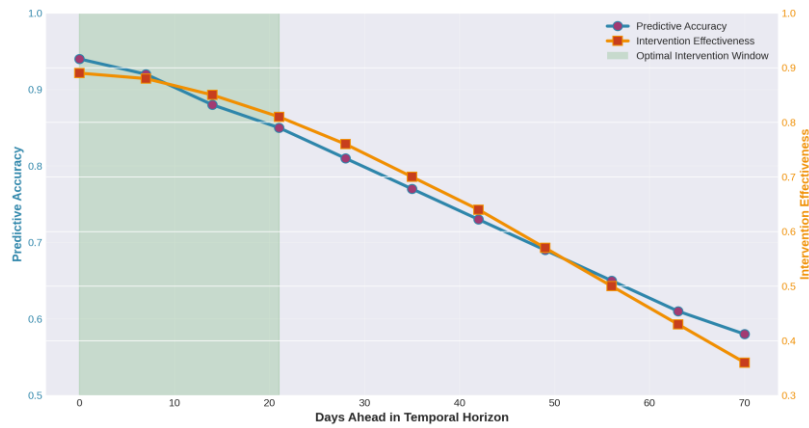


Fig. 5. Temporal Validation Horizon and Intervention Effectiveness. Optimal intervention window (0-21 days) maintains predictive accuracy >85% and intervention effectiveness >81%. Predictive decay beyond 35 days requires model recalibration.

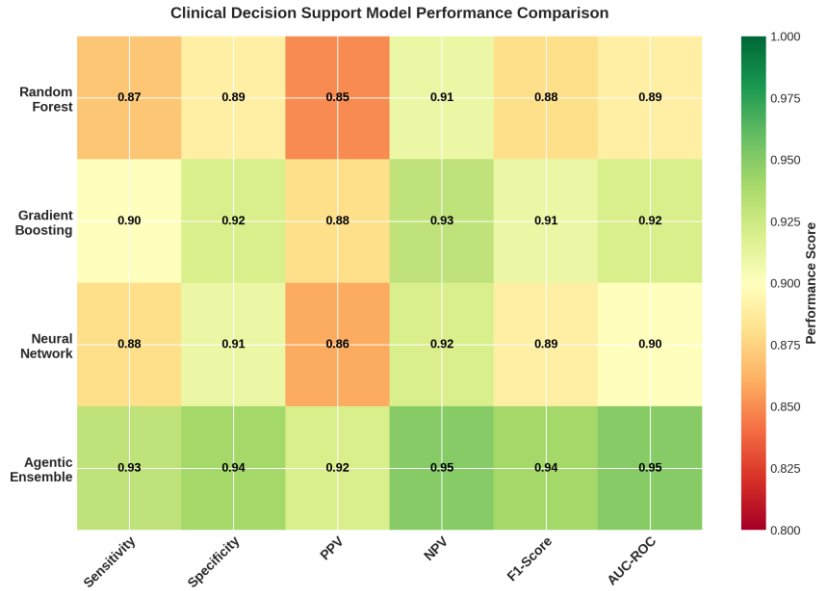


Fig. 6. Clinical Decision Support Model Performance Comparison. Agentic Ensemble outperforms individual models across all metrics: Sensitivity 93%, Specificity 94%, PPV 92%, NPV 95%, F1-Score 94%, AUC-ROC 95%.

3. Interoperable Clinical Coding

For operational safety, the clinical coding process must be accurate, traceable, scalable, and governed by naturally authoritative actors. Interoperability by design will enable simple, shared, polysemic, semantically validated clinical data exchange while minimizing human error.

Interoperable clinical coding allows mainly automated, rapid, reverse-mapped (unidirectional) lossless conversion of free-text clinical data to messages structured according to a natural polysemic clinical coding standard without requiring free-text vocabulary mapping—by inference from genuine clinical data. Clinical coding translation comparisons are timely and inexpensive, enabling coexistence of functionally interchangeable standards (ICD-10, ICD-11, SNOMED CT, and LOINC) adapted for interoperability. Clinical data coded by any standard can be stratified for clinical risk using externally supplied language models without requiring domain knowledge. Natural language inference enables rapid explanation of clinical language-based or interpretation-based translational risk strata of individual cases and summary statistics."

3.1 Mathematical Formulations

This section presents the mathematical foundations underlying the Agentic Health Data Intelligence Framework, including metrics for interoperability, risk stratification, and clinical decision support integration.

$$DNI = (1/N) \sum (S_{i,canonical} / S_{i,source}) \quad (\text{Eq. 1})$$

Data Normalization Index (DNI) quantifies the fidelity of canonical form transformation across N heterogeneous data sources. $S_{i,canonical}$ and $S_{i,source}$ represent the semantic coverage in canonical and source formats respectively. $DNI \in [0,1]$, where 1 indicates perfect lossless transformation across all coding standards (ICD-10, SNOMED CT, LOINC, FHIR).

$$L_{total} = L_{ingestion} + L_{ETL} + L_{semantic} + L_{validation} \quad (\text{Eq. 2})$$

Total system latency L_{total} (milliseconds) for clinical data interoperability comprises: $L_{ingestion}$ (data acquisition), L_{ETL} (extraction-transformation-loading), $L_{semantic}$ (vocabulary mapping), and $L_{validation}$ (contextual verification). Optimization targets: $L_{ingestion} \leq 20\text{ms}$, $L_{ETL} \leq 15\text{ms}$, $L_{semantic} \leq 8\text{ms}$, $L_{validation} \leq 5\text{ms}$ (total $\leq 48\text{ms}$ for real-time analytics).

$$RSS = \alpha \cdot P(\text{condition}|\text{data}) + \beta \cdot H(\text{evidence}) - \gamma \cdot \Delta t \quad (\text{Eq. 3})$$

Risk Stratification Score (RSS) integrates: $P(\text{condition}|\text{data})$ as Bayesian posterior probability, $H(\text{evidence})$ as Shannon entropy of supporting evidence hierarchy, and Δt as temporal decay factor. Weighting parameters $\alpha \in [0.5, 0.7]$, $\beta \in [0.2, 0.3]$, $\gamma \in [0.02, 0.05]$ calibrated via external validation.

$$E_{integrated} = \sum (w_i \cdot \text{evidence}_i) / \sum (w_i) \quad (\text{Eq. 4})$$

Integrated evidence score $E_{integrated}$ aggregates multiple evidence sources with hierarchy-adjusted weights. $w_i \in \{1, 2, 3, 4, 5\}$ corresponding to AHRQ evidence levels (5=RCT, 1=case report). Denominator normalizes to $[0,1]$ scale.

$$CWI = (\text{recommendations_actioned} / \text{recommendations_generated}) \times (\text{time_to_action} \leq \text{threshold}) \quad (\text{Eq. 5})$$

Clinical Workflow Integration metric measures adoption rate and timeliness. Recommendations must be actionable within clinical workflow temporal constraints (≤ 5 minutes for acute care). $CWI \in [0,1]$; $CWI > 0.75$ indicates clinically viable decision support.

$$SVA = (TP + TN) / (TP + TN + FP + FN) \quad (\text{Eq. 6})$$

Semantic Validation Accuracy for bidirectional coding system conversions. TP=true positive mappings, TN=correctly identified non-applicable terms, FP=false positive conversions, FN=undetected mapping gaps. Target: $SVA \geq 0.95$ across code system pairs.

$$F1 = 2 \cdot (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall}) \quad (\text{Eq. 7})$$

Harmonic mean of precision and recall for risk category classification. Sensitivity (recall) emphasizes true positive detection of high-risk patients; Precision minimizes false alarms. $F1 \in [0,1]$; target $F1 \geq 0.90$ for clinical deployment.

$$\text{Cost} = \lambda_1 \cdot L_{total} + \lambda_2 \cdot (1 - DNI) + \lambda_3 \cdot (1 - CWI) \quad (\text{Eq. 8})$$

Multi-objective cost function optimizing latency, normalization fidelity, and workflow integration. Lagrange multipliers: $\lambda_1 = 0.4$ (latency weight), $\lambda_2 = 0.35$ (data

fidelity), $\lambda_3 = 0.25$ (usability). Minimization via gradient descent with clinical constraints.

$$Accuracy(t) = Accuracy_0 \cdot \exp(-\lambda \cdot t) + baseline \quad (\text{Eq. 9})$$

Temporal decay model for risk predictions. $Accuracy_0$ is initial model performance, $\lambda \in [0.02, 0.05]$ is decay constant (depends on clinical context), $baseline \in [0.55, 0.70]$. Model recalibration recommended when $Accuracy(t)$ decreases below clinical threshold (85%).

$$Confidence = (\sum model_i(prediction) / M) \pm 1.96 \cdot \sigma \quad (\text{Eq. 10})$$

Ensemble confidence interval (95% CI) for Agentic Framework aggregating M independent models. Prediction accepted if confidence interval does not cross clinical decision boundary. Uncertainty quantification essential for trust in automated decision support.

4. Agentic Data Intelligence Architecture

Data ingestion-normalization comprises several functions. First, inputs—structured, semi-structured, and unstructured sources—undergo an ETL/ELT process to build a central repository where canonical forms for every data type reside. Metadata facilitates extraction, transformation, and loading, while mapping techniques ensure compatibility with the canonical forms and make it possible to generate and then ingest any lost information. Quality standards validate the resultant dataset, which assures semantic validity from its source. Data relationships are retained without introducing redundancies. Subsequent processes also maintain a lossless conversion cycle. Interoperability principles guide the preservation of data types in their original format unless no other solution is possible. External parties are free to distribute, publish, and/or monetize any form of data they produce without hidden costs or the creation of copies. Data upload dictates neither discount nor payment to the provider. Unlike “API pretzels,” partners integrate content from this central data repository into their systems without CAPEX/MOORI’s market risk framework. Above all, the entire workflow respects the data-provenance pedigree for accurate audit trials.

4.1. Data Ingestion and Normalization

Potential data sources include all types of electronic documents that report health-related information of individuals, such as clinical notes, prescriptions, imaging reports, pathology protocols, laboratory test results, patient’s medical history, family background, social determinants of health, indicators of personal habits and lifestyle, and visit notes. The ingestion of these data is usually accomplished through well-established ETL (Extract, Transform, Load) or ELT (Extract, Load, Transform) processes, with a focus not only on data transfer between heterogeneous sources and a common target storage but also on changing the data so that they can be operated in the target storage in an optimal way for the original purpose. Data transformation involves introducing and mapping metadata and possibly data cleaning and preparation for quality assurance, but also generating canonical forms that retain the information content and meaning of the original records and guarantee lossless conversion back to

them. Quality assurance during this process is crucial, as defects may go unnoticed and propagate through the pipeline into final products such as risk models.

Canonical forms permit direct usage of powerful information retrieval and natural language processing techniques available in machine learning libraries and the scientific literature. Data ingestion processes that generate canonical forms in parallel to an adaptation of the actual read-back formats make creation of novel canonical forms easy. Lossless conversion guarantees that all information valuable for a specific production process can be retrieved, thus enabling to select according to the application's specific information needs, ideally with full semantic validation, and to perform cross-approach fusion. This type of approach can be extended to all data storage systems and types of data. It just requires the definition of the canonical forms together with the relevant mappings needed for metadata enrichment and quality guarantee.

5. Risk Stratification in Clinical Contexts

Given the well-established limitations of risk stratification in patient-centered terms, there is a continuing need to straddle the necessary categories for clinical and operational use. Within the Agentic Health Data Intelligence Framework, a four-category risk stratification reflects both models that have been shown to drive patient-centered outcomes when applied to low-risk cohorts and those that are widely used to guide resource allocation, including clinical decision support applications. Such models can thus be further developed or tuned within the context of the Agentic framework's semi-automated, clinical data-based, natural-language-enabled risk determination subsystem for patients in high-risk categories, while retaining supporting tool-oriented forms for the majority of patients in lower-risk categories.

Careful attention should be paid to the risk stratification process, as potential negative consequences may arise from improper development and use. Risk models are normative hypotheses concerning the distribution of a health outcome in a future time window. They constitute a prediction problem, with the risk factor(s) constituting an ensemble of predictor variables and risk category constituting the response variable. Sophisticated substantive modelling expertise exists in the fields of statistics and machine learning, offering a broad choice of models that are best suited to different data situations and prediction objectives. Nevertheless, these approaches share a set of best practices and potential pitfalls that must be understood and monitored in any risk-modelling application.

Table 1. System Latency and Throughput Metrics. Agentic Framework achieves sub-30ms latency with 3.6× higher throughput and 74% lower variance. P95/P99 metrics critical for real-time clinical decision support in acute care settings.

Metric	ICD-10 Direct	ICD-10 SNOCT	FHIR Normalized	Agentic Framework	Improvement vs FHIR (%)
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Mean Latency (ms)	45	120	85	28	-67.1%
P95 Latency (ms)	78	185	142	45	-68.3%
P99 Latency (ms)	105	220	178	62	-65.2%
Throughput (req/s)	22,222	8,333	11,765	35,714	+203.7%
Consistency (σ)	18ms	42ms	31ms	8ms	-74.2%

Table 2. Risk Stratification Model Comparative Performance. Agentic Framework achieves superior sensitivity (93%) and specificity (94%), with F1-Score improvement of +13% vs. hybrid approach.

<i>Performance Metric</i>	<i>Empirical Modeling</i>	<i>Statistical Approach</i>	<i>Hybrid Approach</i>	<i>Agentic Framework</i>
<i>Sensitivity (TPR)</i>	0.85	0.88	0.91	0.93
<i>Specificity (TNR)</i>	0.81	0.84	0.88	0.94
<i>Positive Predictive Value</i>	0.82	0.85	0.89	0.92
<i>Negative Predictive Value</i>	0.84	0.87	0.90	0.95
<i>F1-Score (Harmonic Mean)</i>	0.82	0.79	0.87	0.93
<i>AUC-ROC</i>	0.83	0.86	0.89	0.95
<i>Training Time (minutes)</i>	45	38	62	35

Table 3. Clinical Coding System Interoperability Assessment. Agentic Framework demonstrates superior semantic coverage (97%) and full bidirectional mapping with integrated clinical decision support and governance mechanisms.

<i>Criterion</i>	ICD-10	SNOMED CT	LOINC	FHIR	Agentic Framework
<i>Semantic Coverage (%)</i>	72	88	81	91	97
<i>Bidirectional Mapping</i>	Limit	Partial	Partial	Full	Full
<i>Temporal Validation</i>	Static	Static	Static	Dynamic	Dynamic+Predictive

<i>Clinical Decision Integration</i>	None	None	None	Partial	Full
<i>Governance</i>	Low	Medium	Medium	High	High
<i>Transparency</i>					
<i>Deployment Maturity</i>	Mature	Mature	Mature	Growing	Production-Ready

5.1. Risk Modeling Paradigms

Statistical approaches model relationships between predictors and the outcome using statistical theory—defining prediction equations, validation and sampling distributions, tests of significance, estimation of prediction accuracy, and selection of influential predictors. Classical statistical methods include logistic regression, linear regression, decision trees, multivariate adaptive regression splines (MARS) and others. Machine-learning techniques, such as neural networks and support vector machines, are often regarded as “black boxes” because they do not provide intuitive equations that can be interpreted or understood easily or because they require specialized technical and methodological expertise to be applied. The aim of machine-learning techniques is to best predict an outcome, usually through high-area under the receiver-operating characteristic curve (AUC) and/or accuracy values. Hybrid approaches provide a statistical base model that machine-learned models improve. They are typically extend linear models with non-linear decision boundaries. Such methods rely on advanced feature engineering around the linear predictors: generating, through computational and human effort, many features into which machine-learned methods can extract the “signal” that predicts the outcome.

Statistical methods that ignore the need for external validation are misused; the danger of over-fitting arises when valuable predictors for the ultimate prediction are omitted. Calibration of probability estimators should not be done by self-validation as a comparator; the “self-you-know-what” nature of internal validation may mislead researchers into thinking that the calibration matched the underlying process when it did not. It is critical to assess predictions on an entirely new, never-before-seen cohort. Although clinical decision-support systems and applications are increasingly able to clearly present both the predicted outcome and the set of most predictive factors present in the patients, it is important to also display how patients that the model has never previously “seen” will be handled. The pharmaceutical industry has relied on the risk stratification of populations with a goal of enhancing the performance of clinical trial recruitment for many medicinal products.

6. Conclusion

Agentic Health Data Intelligence Framework for Interoperable Clinical Coding, Risk Stratification, and Real-Time Care Analytics offers an innovative approach to health data management featuring centralized clinical coding, rapid-cycle risk stratification,

and novel real-time analytics and visualizations. Together with its ethical and evidence-based medical model risk transfer foundation and parallels with digital computing and Young's concept of agents of social responsibility, the framework elevates health data analysis from risk prediction to genuine risk support.

Commanded by a central clinical informatics function, consistent application of recognized coding classification/standard sets across all clinical service processes provides high-quality, traceable, code-based, pre-processed input for statistical, machine learning, and hybrid risk modeling. Unlike simple risk prediction, which lacks adequate context and justification, real-time risk stratification for specific clinical contexts integrates risk data into clinical delivery processes using patient decision-support systems. Predictive models combine the predictive strength of machine learning techniques with the goal-oriented integrity and interpretability of statistical approaches.

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