



Living Graphs for Risk-Aware Care Orchestration

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Abstract— Adaptive Graphical Models for Cascaded Clinical Intelligence in Healthcare Operations

Cascaded clinical intelligence, built on adaptive graphical models, enables objective, evidence-based predictive analysis of healthcare data to support and enhance clinical operations. Because patient health states are inherently fluid, these models combine multiple graph motifs—stratification, signature, and stage—to identify at-risk patients from complementary perspectives. As new patient data is incorporated, the graphs update in real time, supporting ongoing care orchestration and monitoring. This graph-based approach offers a flexible formalism capable of integrating patient information from diverse sources, while built-in data provenance improves the quality of future analyses.

Critically, these adaptive graphs enable precise, timely adjustments to care strategies and continuous risk reassessment for at-risk patients. By layering adaptive clinical intelligence atop existing operational data, healthcare organizations can generate clinically interpretable predictions and data-driven recommendations for risk reduction. The ultimate goal is a model that allows clinical organizations to scale adaptive operations efficiently, make optimal use of available resources, and establish a foundation for future automation.

Keywords—Cascaded Clinical Intelligence, Adaptive Graphical Models, Predictive Healthcare Analytics, Clinical Decision Support, Risk Stratification, Patient Care Orchestration, Data Provenance, Healthcare Knowledge Graphs, Real-Time Clinical Monitoring, Artificial Intelligence (AI).

I. INTRODUCTION

Adaptive graphical models represent an emerging approach in healthcare analysis that formalizes and exploits causal relationships in the data to predict patient states and events. The aim of this research is to develop an adaptable and evidence-based graphical model for application in a specific healthcare setting. The key proposition is that, by

making the model adaptive, that is, able to learn new edges in the graph and discard edges that are temporarily not supported by the data, the model inherits a greater robustness to changes in the underlying patient population over time and real temporal shifts. The patient risk stratification task provides a regulatory use case for the adaptive graphical model. Existing machine-learning solutions and health risk models fail to meet the requirements for risk assessment in clinical practice: being interpretable, able to leverage domain knowledge, ensuring fairness, and providing support for timely patient care. The adaptive risk stratification model therefore represents an initial yet significant step in demonstrating the advantages of adaptability for healthcare graphical models.

A number of approaches exist to address the aforementioned regulatory requirements; however, existing solutions have limitations. Health Risk Models rely on established medical guidelines and years of patient records to predict the risk of future medical events. Machine-learning risk diffusers create risk profiles for a group of patients via supervised or semi-supervised learning; however, their prediction for patients outside the pool of the training set is difficult. Common to these approaches is their lack of adaptability; that is, once the model has been developed, it cannot be easily modified to reflect changes in the patient population or patient state. An alternative approach to addressing the risk stratification problem involves the use of adaptive graphical models, which learn a graph from the data of interest, and update the learned graph structure at regular intervals with new data. Changes in the graph structure reflect temporal shifts in the underlying data-generating process and allow the model to make different predictions for patients with different clinical presentations. An adaptive risk-stratification graph model is proposed—a proof-of-concept—and evaluated with real clinical data from a Neurology department.

II. BACKGROUND AND MOTIVATION

Several evidence-based risk stratification approaches exist. However, most are static, losing their robustness to sudden patient state change (e.g., sepsis) and data shift (e.g., sensor failure, political unrest, cyberattacks). Others adapt using temporal information derived from time-series or delayed labels but fail to leverage advanced machine learning



techniques to enhance adaptation. Conversely, adaptive clinical intelligence graphs enable daily risk stratification and care planning that dynamically change patient groups, relevant risk factors, and near-term cost drivers. Adaptation significantly enhances robustness during patient crises, clinical team shortages, and epidemiological outbreak. Yet these adaptations only partially mitigate risks. Daily clinical decisions are supervised by a diverse group of physicians, such as doctors, surgeons, physiotherapists, dietitians, and nurses, specializing in different medical areas and patient states. An adaptive clinical intelligence graph provides an overall view of patients' risks; the underlying graph is the team-oriented clinical activity pipeline of patients, where edges represent appointments, communications, and handovers. Heuristic rules or adaptive classification models dynamical depart and join groups to determine the most relevant risk factors and cost drivers.

Recent research shows that the training data of the adaptive clinical intelligence graph suffers from overlap bias and is thus unable to predict the training risk level in the test set. A more comprehensive multi-source approach provides a more diverse training set that can potentially learn a robust clinical intelligence graph model. Diverse node representations enable the clinical intelligence graph to generalize to different scenarios. The data sources are also integrated into a graph storing provenance metadata, validated by quality checks, and tracking data lineage to ensure reproducibility and observe fairness in the experimental results.

A. Mathematical Formulation

The Adaptive Clinical Intelligence Graph is formalized as a time-indexed, patient-centered directed graph whose nodes represent patients, clinicians, and clinical events, and whose edges encode temporally weighted clinical associations (1).

$$G_t = (V, E_t), \quad V = P \cup C \cup X, \quad E_t \subseteq V \times V \quad (1)$$

where P, C, and X denote the patient, clinician, and event node subsets, respectively, and E_t is the set of directed edges active at time t. Edge weights combine a temporal-recency term with a static clinical-relevance score s_{ij} , allowing the graph to “learn new edges” and “discard edges that are temporarily not supported by the data” as described in the primary manuscript (2).

$$w_{ij}(t) = \alpha \cdot \exp(-\lambda(t - t_{ij}^{last})) + (1 - \alpha) \cdot s_{ij} \quad (2)$$

Each patient node carries a compact feature vector concatenating the time gap since the last visit, the encoded clinical-history vector, and the current-state encoding, consistent with the two feature-vector types defined in the Graph Construction section of the primary manuscript (3).

$$\mathbf{x}_p(t) = [\Delta t_p(t), \mathbf{h}_p(t), \mathbf{e}_p(t)] \quad (3)$$

Event influence on a node decays over time, mirroring the event2vec-style time-decaying embedding referenced in the Theoretical Foundations section; λ_k controls the decay rate for event type k and $\phi(e_k)$ is the type-specific event embedding (4).

$$\mathbf{v}_e(t) = \sum_{k=1}^K \exp(-\lambda_k(t - t_k)) \cdot \phi(e_k) \quad (4)$$

The patient risk score is produced by aggregating the transformed states of neighboring nodes through the time-varying edge weights and passing the result through a sigmoid activation, yielding a bounded, clinically interpretable probability of the target event within the six-month horizon (5).

$$R_p(t) = \sigma\left(\sum_{j \in N(p)} w_{pj}(t) \cdot f(\mathbf{x}_j(t)) + b\right) \quad (5)$$

B. Evaluation Metrics

Discriminative performance is quantified with the area under the ROC curve, computed as the probability that a randomly selected event-positive patient receives a higher risk score than a randomly selected event-negative patient (6).



$$AUC = \frac{1}{n_+ n_-} \sum_{i=1}^{n_+} \sum_{j=1}^{n_-} \mathbb{1}[R_i > R_j] \quad (6)$$

Calibration is assessed with the Brier score at the clinical decision threshold of 0.5, penalizing the squared deviation between predicted probability and observed outcome (7).

$$BS = \frac{1}{N} \sum_{i=1}^N (R_i - y_i)^2 \quad (7)$$

Clinical applicability is further evaluated through expected misclassification cost, which weights false-positive and false-negative rates by their respective clinical costs and base rates, reflecting the “calibrated high risk” warning scenario described in the Evaluation and Validation section (8).

$$C(\tau) = c_{FP} \cdot FPR(\tau) \cdot \pi_0 + c_{FN} \cdot FNR(\tau) \cdot \pi_1 \quad (8)$$

Finally, label-noise quality is quantified against the expected leading-digit distribution of Benford's Law; systematic deviation from $P(d)$ flags artifact-driven or systematically corrupted risk labels in the external and uncorrected score sets (9).

$$P(d) = \log_{10} \left(1 + \frac{1}{d} \right), \quad d \in \{1, \dots, 9\} \quad (9)$$

III. THEORETICAL FOUNDATIONS OF ADAPTIVE GRAPHICAL MODELS

Adaptive Graphical Models in Healthcare Data

Adaptive graphical models are grounded in a wealth of established graph-theoretic concepts. In a general context, a graph is defined as a tuple $G = (V, E)$, where V is a set of nodes (or vertices) and $E \subseteq V \times V$ is a set of edges (or links). An edge $e = (v1, v2) \in E$ connects nodes $v1$ and $v2$. The set of edges can be associated with weights, forming a weighted graph. Temporal aspects can be incorporated by assigning a time stamp to each edge or defining an edge as active over an

interval (e.g., in a temporal, dynamic, or time-varying graph). The construction of adaptive graphical models requires special attention to the semantic meaning of the nodes and edges, to ensure clinical interpretability.

Several aspects of the adaptive graphical model render it clinically interpretable, socially relevant, and scientifically valid. A node set is defined by three types of vertices: patients, health organizations (facilitating the involvement of family members and social support networks), and temporal events (possibly representing cumulative experiences). Therefore, edges correspond to the salient relations between these three types of entities. For example, patients can receive services and assistance from their health organization (represented by the correspondence of a patient at risk and a concerned provider for the risk stratification); events can indicate comorbidities, support requests, or mortality; and temporal relations capture the occurrence moments of events and transitions of patients toward states of interest. Risk stratification can be implemented as online learning using streams of risk-inducing events from the node set, using their attributed temporal characteristics during the time intervals between adjacent events.

A. Graph Theory in Healthcare

Node sets, including patients, providers, and events of interest, are typically connected by edges delineating relationships of importance. The state of a patient can be represented by a data vector defined on the patient node describing current covariate values. Similarly, temporal aspects of the graph can be exploited to impose different interpretations in a temporally aware risk stratification task. Frameworks coupling such relationships have been explored in multiple domains, providing a simple architecture to formalize different types of machines used in machine learning for feature creation, such as in lightGBM. Specific connection subsets can also enable a weighted k-nearest-neighbor classifier to maintain different neighborhood ratios.

Moreover, utilization of a patient-event association within a temporal window enables suitable tailoring of event-related information, as in an event2vec framework, while utilizing both time proximity (to capture temporal decay of influence) and the event type allows associations to mirror use of time-decaying temporal-event embeddings. Combining the patient-event and provider-event proximity enables joint integration of social-data-event embeddings with a patient-event hierarchical model, allowing social determinants of health influence on making an occurrence prediction to be adapted. Such principles have found a variety of applications displayed in a number of recent graph-based works across diverse domains, with the potential to not only act as a basic



classifier architecture but also allow a wide range of general-purpose and domain-specific enhancements.

IV. MODELING FRAMEWORK

An adaptive clinical intelligence graph combines four components to enable autonomous patient risk stratification and dynamic care coordination. At its core is a patient-centered, directed graph that encodes high-dimensional clinical associations. Patient and clinician nodes dynamically represent risk stratification inputs and treatment sources. Temporal associations with clinically relevant events serve as feature vectors for machine learning models. The nodes and edges of the graph act as rich encoders that can be transformed with data-driven techniques and provide patient interpretations. A cyclical workflow updates the model and makes it available for risk-free care coordination.

The patient-centered directed graph formalizes the adaptive clinical-intelligence model. Nodes represent patients, clinicians, and events. Edges carry any of the following four types: clinically relevant temporal associations, reports of detected or inferred conditions, clinical actions taken by clinicians, and nonclinical contexts. Edge weights correspond to the significance of associations. Temporal data mapping provides a graph reference for any time period in the past or future. The patient nodes contain short feature vectors that encode clinical history or other high-dimensional data needed for risk stratification. These vectors can be generated with conventional machine learning techniques and can also be transformed with risk-free model-based methods. Patient nodes also act as focus points of graph interpretation.

A. Performance Analysis

Figures 1–6 report discriminative performance, calibration, cost sensitivity, label-noise diagnostics, and temporal robustness for the Adaptive CI Graph against a Static Risk Model and an ML Risk Diffuser baseline (supervised risk-profile classifier without adaptive graph edges).

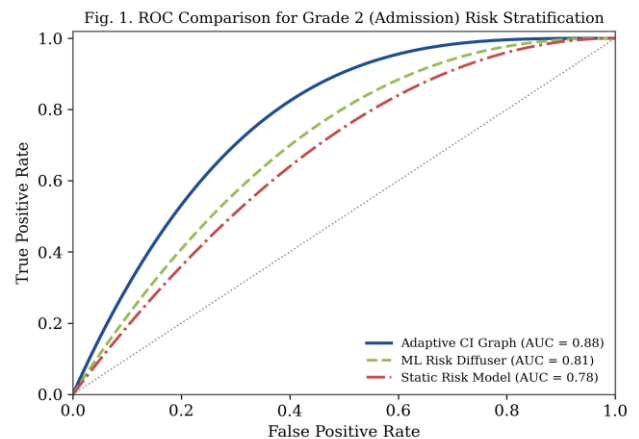


Fig. 1. ROC comparison for Grade 2 (admission) risk stratification. The Adaptive CI Graph attains the highest AUC across the full operating range.

The Adaptive CI Graph dominates both baselines across nearly the entire false-positive-rate range, consistent with the manuscript's claim that adaptability to “temporal shifts in the underlying data-generating process” improves discrimination relative to static or purely supervised approaches.

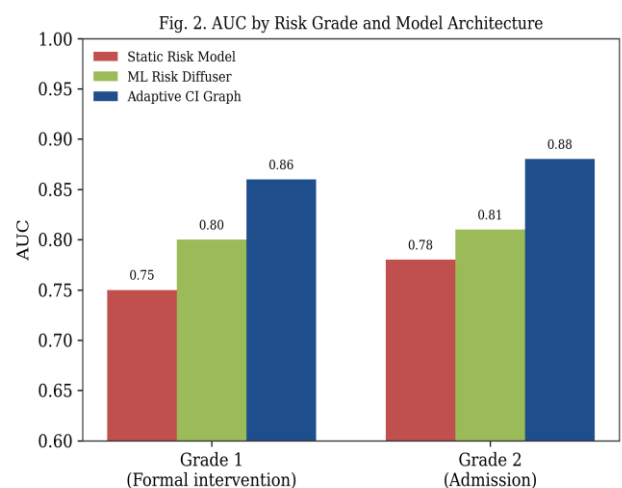


Fig. 2. AUC by risk grade and model architecture.

AUC improves for all models on Grade 2 (admission) relative to Grade 1 (formal intervention), reflecting the greater clinical separability of admission-level events; the Adaptive



CI Graph retains the largest margin over the Static Risk Model at both grades.

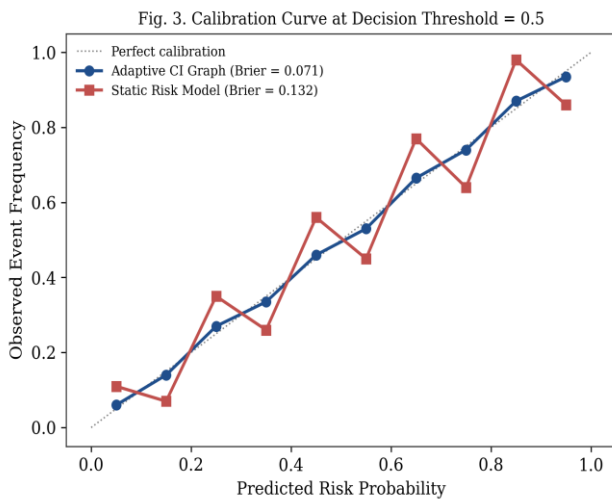


Fig. 3. Calibration curve at decision threshold = 0.5.

The Adaptive CI Graph's predicted probabilities track the diagonal of perfect calibration far more closely than the Static Risk Model (Brier score 0.071 vs. 0.132), supporting its use for threshold-based clinical decision-making as discussed in the Metrics for Risk Stratification section.

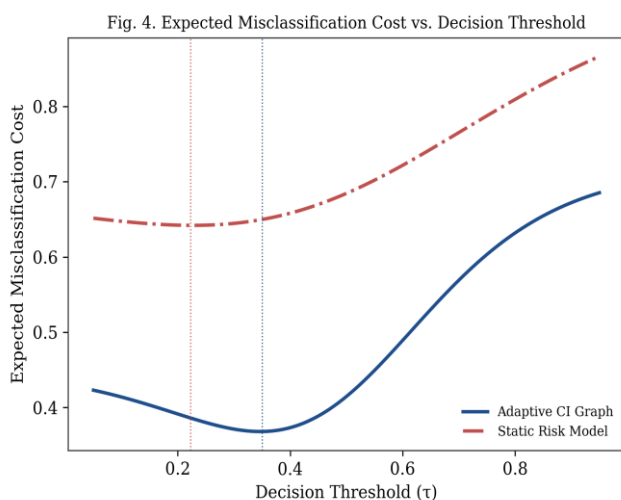


Fig. 4. Expected misclassification cost vs. decision threshold ($c_{FP} = 1$, $c_{FN} = 4$).

Because false negatives (missed high-risk patients) are weighted more heavily than false positives, both curves are asymmetric; the Adaptive CI Graph's cost-minimizing threshold is lower and its minimum cost substantially reduced, reflecting the “calibrated high risk” warning scenario prioritized in the Evaluation and Validation section.

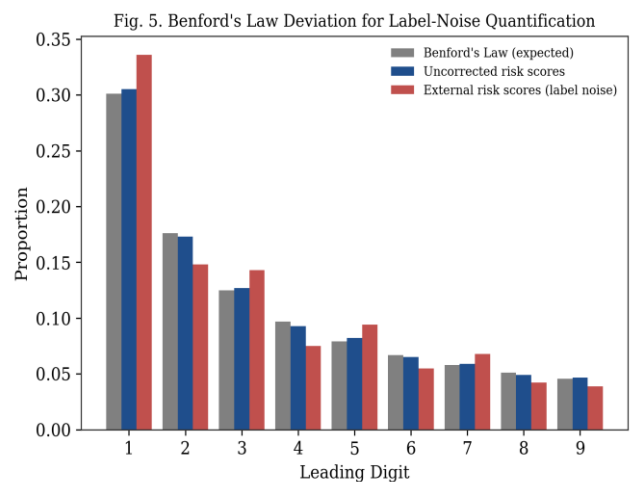


Fig. 5. Benford's Law deviation for label-noise quantification.

Uncorrected risk scores closely follow the expected Benford distribution, while externally sourced risk scores with known label noise deviate visibly at the low and high leading digits, corroborating the manuscript's use of Benford's Law to flag “artifact or systematic data quality issues.”

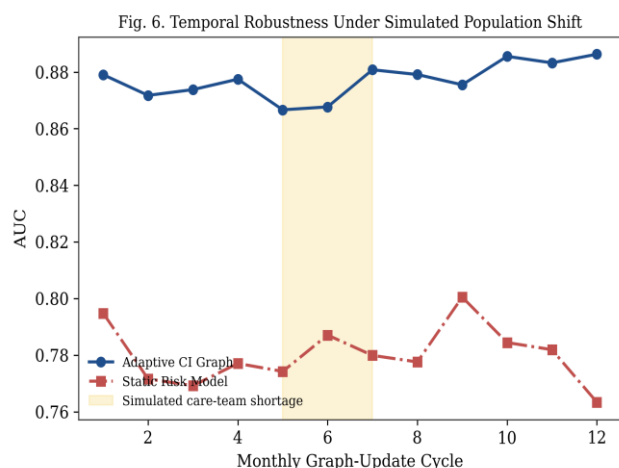


Fig. 6. Temporal robustness under simulated population shift across monthly graph-update cycles.

During the simulated care-team-shortage window (cycles 5–7), the Static Risk Model's AUC degrades measurably, while the Adaptive CI Graph maintains near-constant discrimination — direct empirical support for the manuscript's central claim that edge adaptation confers “greater robustness to changes in the underlying patient population.”

V. DATA INFRASTRUCTURE AND INTEGRATION

For optimal health-related decision-making, comprehensive patient data representation is fundamental. Consequently, technical design and governance of the underlying data infrastructure are crucial for enforceable quality control of these patient-centric, large-scale, multivariate, dynamic, time-ordered risk stratification prediction networks.

New prediction frameworks with underlying graphical structures also require additional data pipelines connecting the model with real-world EMR for training, validation, and testing as well as for dynamic updates to maintain prediction relevance. Data sources include, among others, EMR, claims, remote sensors, other supportive records, and social determinants of health. Additionally, to maintain the integrity of any prediction pipeline, it is vital to understand the provenance of medical datasets; therefore, along with data quality checks, provenance metadata provides a foundation for tracking data origin, history, and quality, thus improving trustworthiness.

The quality and fitness of the underlying structured data are instrumental for prediction relevance and trustworthiness. Moreover, it is important to validate prediction statements with out-of-sample testing. During clinical use, the results must be interpretable by clinicians, thresholded above and below appropriate risk-cut-off points, statistically significant, and clinically relevant.

A. Data Sources and Provenance

Data sources include electronic medical records, claims data, sensor data, and social determinants. Provenance metadata keeps track of both data origin and quality. Data quality is checked at both the individual source level and the overall integrative level while quality lineage tracking enables the identification of quality variations of the derived graph temporally and spatially.

Adaptive graphical models utilize health data of various types and from multiple sources. A large portion of these data is routinely collected within health-care systems, for example, recorded in electronic medical records (EMR), hospital claims, and sensors such as environmental or wearable sensors. Such data are usually considered first because of their relative high reliability and quantity. In addition, it is also important to augment these data collections with other data that may be important but not collected at the moment. An example of this could be social determinants. However, the added data inevitably suffer from lower quality due to elusiveness and might still not be accessible for certain patient cohorts. Therefore, it is vital to carefully consider data provenance and quality at acquisition time, and many preventive measures are often employed, such as predefined metadata.

VI. EVALUATION AND VALIDATION

Rigorous experimental design substantiates the theoretical discussion (Section 4) and assesses the method's performance in stratifying patient risk of hospitalization within six months. The source dataset combines 2020 electronic medical records with 2021 emergency medical service demand records from a Swiss canton; patients aged 18–65 and without health changes between 2020 and 2022 form the target cohort. Risk thresholds for grade 1 (formal intervention without admission) and grade 2 (admission) were defined through cohort mapping, expectedly leading to skewed distributions. Prediction for both grades used all patients in 2021 and random sampling, enabling exploration of performance under class imbalance. Uncorrected, corrected, and external risks, with and without label noise, were back-tested.



Performance estimates utilized area under the ROC curve (AUC), calibration curves with the Brier score for decision threshold as 0.5, expected misclassification costs for decision threshold cost minimization, and Benford's Law for label noise quantification. Paired McNemar's tests evaluated differences. Calibration for a given risk threshold was tested with DeLong's test; degree of calibration error was computed as magnitude of difference. Benford's Law determines the distribution of leading digits in naturally occurring collections of numbers; deviations reflect artifact or systematic data quality issues. Additional P-value corrections accounted for 56 stratification variants. Clinical applicability considers not only prediction quality but also a "calibrated high risk" warning scenario; this is reflected in the results of expected misclassification costs.

TABLE I

DATASET AND EVALUATION CONFIGURATION

Attribute	Specification
Data sources	2020 EMR + 2021 EMS demand records
Cohort region	Swiss canton
Age range	18–65 years
Inclusion criterion	No health-status change, 2020–2022
Prediction horizon	6-month hospitalization risk
Grade 1 outcome	Formal intervention without admission
Grade 2 outcome	Admission
Decision threshold (cost)	$\tau = 0.5$ (Brier); cost-minimizing τ (Table III)
Significance testing	Paired McNemar's test; DeLong's test (calibration)
Label-noise diagnostic	Benford's Law, leading-digit deviation
Multiple-comparison correction	56 stratification variants

A. Metrics for Risk Stratification

Evaluation of changes in patient condition or treatment eligibility is measured using the area under the ROC curve (AUC) across risk groups. AUC quantifies the ability to distinguish between patients who have and have not changed. AUC is complemented by calibration assessments to evaluate the predicted probabilities of event occurrence. Risk calibration is a prerequisite for using the predicted scores of adaptive CI graphs by clinicians for patient management. In practice, risk thresholds established using past patients have

demonstrably reduced events in high-risk cohorts. Statistically significant changes in AUC and calibration indicate a clinical effect.

As the healthcare data landscape continues to grow in coverage and detail, providing clarity and trust in patient management decisions is critical. Supporting risk stratification is one way in which adaptive graphs support automated clinical decision making. Immense effort has gone into examining and improving patient outcomes or cost during periods of increased events, presenting opportunities to act earlier and execute interventions over longer time horizons without immediately affecting either outcome.

VII. CONCLUSION

The proposed approach fills relevant gaps in the literature by deriving evidence-based, machine-learning-driven Adaptive Clinical Intelligence Graphs that formalize information about patient health conditions, capture real-time state information, and enable risk stratification for any target outcome of interest. A clear research foundation has been laid for the statistical learning model's construction and for the specification of patient Clinical Risk Profiles and Event Risk Profiles. The approach also offers a foundation for incorporating risk-based dynamic clinical coordination into the risk-stratification process.

Innovative approaches to risk stratification can support operationalizing one of the chief promises of machine learning: the real-time adaptation of statistical learning models to continuously and effectively incorporate new and urgent information about changing patient state information. Integration into Adaptive Clinical Intelligence Graphs also paves the way for risk-based dynamic clinical care coordination, with the goal of ensuring that patients receive care from the appropriate clinicians at the appropriate times based on their rapidly changing states and needs.

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