ISSN: 3067-1140

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 01 ISSUE: 01

RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

Predictive Risk Stratification in Health Insurance Populations

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Abstract

Predictive analytics seeks to identify future risks and opportunities for individuals and groups. In a population health risk stratification context, addressing the higher level of risk associated with a subpopulation creates the potential for improved outcomes and reduced costs. The proposed study aims to improve predictive analytics for hospital admission, readmission, and emergency department (ED) visit risk stratification in an insurance network using advanced methodologies. Primary data sources from claims and provider networks provide the foundation for prediction and the design of use cases to support the predictive engine. Sensitivity analyses assess predictive equity along social determinant lines to ensure fairness. Model performance is measured in terms of the receiver operating characteristic, precision-recall, F1 score, area under the precision-recall curve, and Matthews correlation coefficient. Results could influence resource allocation, care management priorities, contracting, and network design.

Population health risk stratification identifies clusters of individuals with shared health risk characteristics for prioritizing health care actions and interventions. Care management interventions are generally devoted to individuals in specific need categories—those at risk of hospitalization for specific acute or chronic conditions, recently discharged from the hospital, facing social or economic barriers to achieving good health, receiving end-of-life support, or dealing with multiple medical conditions—and the overall levels and distribution of illness burden and acuity can inform the investment and allocation of resources across these care pathways. Predictive analytics seeks to identify future risks and opportunities for individuals and groups. In a population health context, addressing the higher level of risk associated with a subpopulation creates the potential for improved outcomes and reduced costs.

Keywords: Population Health Analytics, Risk Stratification Models, Predictive Healthcare Analytics, Hospital Readmission Prediction, Emergency Visit Prediction, Claims Data Analytics, Provider Network Analytics, Health Risk Modeling, Care Management Optimization, Social Determinants of Health, Predictive Equity Analysis, Healthcare Resource Allocation, Clinical Risk Prediction, Outcome Optimization Models, Precision-Recall Metrics, ROC Analysis, F1

Score Evaluation, Healthcare Data Science, Insurance Network Analytics, Data-Driven Care Management.

1. Introduction

Recent advances in data science and machine learning provide an opportunity to move beyond classical methods of predictive analytics in the field of population health risk stratification. Population health risk stratification uses predictive analytics to categorize large populations of patients into different levels of health risk from adverse outcomes, thereby enabling better resource allocation and care management by health systems. Predictive analytics for population health risk stratification has not yet been applied for organizations such as insurance networks who do not directly provide patient care but nevertheless bear the financial risk associated with the networked care of patients. The aim of this project is to develop population health risk stratification within insurance networks to manage risk more effectively and improve risk-adjusted care outcomes.

Risk stratification based on predictive analytics uses historical data to predict future patient health needs, enabling a more effective allocation of resources to meet patients' diseases and to better manage comorbid patients within insurance companies. Implementation into the operations and care management workflows of the insurance networks enables support for decision-making around resource allocation and network design. Population health risk stratification enables risk-based management of patient populations who are at higher risk of adverse outcomes. Such risk-based patient management can assist not only health insurers like Connecticut's Health Insurance Exchange but also downstream health systems like hospitals and outpatient groups whose care of these high-risk patients tends to determine their success or failure in value-based contracts.

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AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
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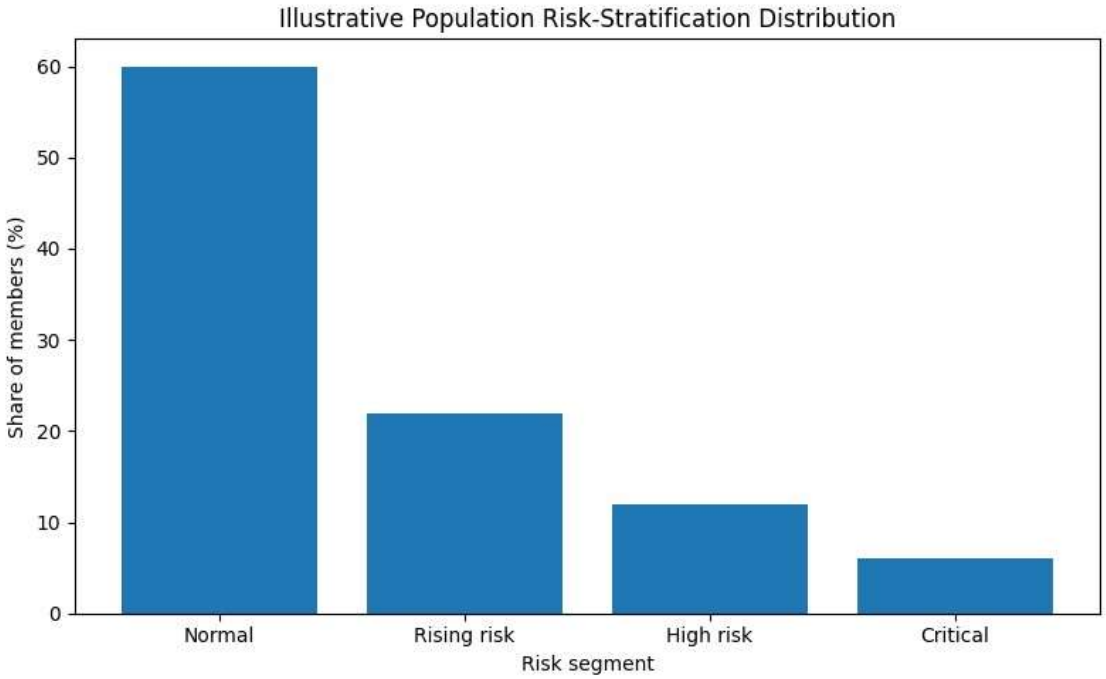

2. Objectives and scope

A data-driven framework for risk stratification is proposed within insurance networks, aligning population health analytics with stakeholder requirements. Governance, workflows, engagement, and fairness across protected attributes are prioritized. Predictive performance, impact on care management, stratification fairness, and augmented networks are examined.

Population health risk stratification is delineated as the grouping of individuals to foster network or system resource allocation, care coordination, or care intervention decision support. The resultant assignment should be predictive of care utilization, expenditure, or health risk. Acuity denotes disease severity and prognosis for the following years, while comorbidity reflects anticipated healthcare utilization in the forthcoming year. Stratification aims to identify groups that warrant care delivery or intervention beyond usual standards, through additional resources within the dedicated care pathway, or by channeling patients to a suitable module among care delivery partners. Population health foresight enables preparation for changing patient demand. Stratified networks can offer care at a lower cost while sustaining or improving outcomes.

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The proposed framework serves policy and practical purposes, informing insurers, providers, and patients. Performance is evaluated through prediction accuracy and fairness across protected attributes. Enhanced risk-adjusted outcomes, via improved population health, should translate to better financial performance for the insurer, validated against external datasets. The scope encompasses community health data management and reduction of health inequity. Population health concepts informing stratification—risk, acuity, comorbidity, and scheme definition—are summarized as a precursor to method comparison.

2.1. Framework for Data-Driven Population Health Risk Stratification

Data-driven population health risk stratification delineates disease risk groups, guiding targeted resources for population segments—normal, rising risk, high risk, and critical condition—through specialized care pathways. A comprehensive data foundation captures the multifaceted drivers of health. Data from insurance networks—claims, enrollment, electronic health record, provider—andre dynamic in combination, yet specific to longitudinal health events. Stratification encompasses four aspects: enabling, predictive, fairness, and operational.

First, predictive models leverage longitudinal elements, identifying care pathway determinants and specifying supporting intervention criteria. Second, predictive performance of future health course, module interconnections, fairness in diversity and exclusion, and operational feasibility and impact on care management control model quality. Third, fairness evaluations consider bias detected in predictive models applied to distinct population segments, ensuring equity of outcomes in stratification-driven management interventions. Fourth, operational importance focuses on scheduling of preventive potential and corrective need modules within health trajectories.

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Fig 1: Transforming Healthcare with Risk Stratification

3. Methodology

In the era of modern medicine, the traditional role of risk stratification models in identifying patient risk is being replaced by predictive models designed to identify patients most likely to benefit from interventions. Little effort has been made to build such models within insurance networks where information asymmetry is minimized and integrating the models into care management is theoretically straightforward. A data-driven framework for risk stratification that defines roles for ethical governance, seamless model integration, and clear decision support is proposed. Risk and population health concepts are defined, and the relevant data elements outlined. Clinical pathway mapping links data elements with care pathways, while data module interoperability is defined to support flexible resource allocation. Finally, fairness in predictive analytics and the policy, clinical, and organizational dimensions required for successful implementation within insurance networks are considered.

Modern approaches to predictive analytics operationalize risk stratification models by identifying patients who would benefit from targeted interventions. In insurance networks, where data integration is optimal and missed opportunities for care management may be expensive, the

need for predictive models is particularly evident. Interactive machine learning, however, requires a continuous source of valuable information and the definitional rigor to keep models current, relevant, and fair. The risk stratification methodology proposed here seeks to achieve both. It delineates the necessary and sufficient conditions for successful implementation, thereby seeking to assist those responsible for data management, analytics, care management, service delivery, and network design. The analysis considers ethical issues along with the practical, clinical, and organizational dimensions required for effective execution.

Equation 1: Logistic regression for admission/readmission/ED-event risk

The **logistic regression** as a standard predictive approach for binary outcomes.

Let:

- $Y_i \in \{0,1\}$, where $Y_i = 1$ means the event occurs for patient i
- $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ are predictors
- $p_i = P(Y_i = 1 \mid x_i)$

We start by assuming the **log-odds** is linear in predictors:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$$

Using the inverse-logit transformation, derive p_i.

Step 1: Exponentiate both sides

$$\frac{p_i}{1-p_i} = e^{\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}}$$

Let

$$z_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$$

Then:

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$$\frac{p_i}{1-p_i} = e^{z_i}$$

Step 2: Multiply both sides by $(1 - p_i)$

$$p_i = e^{z_i}(1 - p_i)$$

Step 3: Expand the right side

$$p_i = e^{z_i} - e^{z_i}p_i$$

Step 4: Move the p_i-terms together

$$p_i + e^{z_i}p_i = e^{z_i}$$

Factor p_i:

$$p_i(1 + e^{z_i}) = e^{z_i}$$

Step 5: Solve for p_i

$$p_i = \frac{e^{z_i}}{1 + e^{z_i}}$$

Equivalent form:

$$p_i = \frac{1}{1 + e^{-z_i}}$$

So the logistic prediction equation is:

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})}}$$

This is the probability model for a binary event such as hospitalization, readmission, or ED utilization.

Likelihood derivation

Since $Y_i \sim \text{Bernoulli}(p_i)$,

$$P(Y_i = y_i) = p_i^{y_i}(1-p_i)^{1-y_i}$$

For n independent patients, the likelihood is:

$$L(\beta) = \prod_{i=1}^{n} p_i^{y_i}\,(1-p_i)^{1-y_i}$$

Take logs:

$$\ell(\beta) = \log L(\beta) = \sum_{i=1}^{n} [y_i \log p_i + (1-y_i)\log(1-p_i)]$$

Substitute $p_i = \frac{e^{z_i}}{1+e^{z_i}}$.

First compute:

$$\log p_i = \log\left(\frac{e^{z_i}}{1+e^{z_i}}\right) = z_i - \log(1+e^{z_i})$$

and

$$1 - p_i = 1 - \frac{e^{z_i}}{1+e^{z_i}} = \frac{1}{1+e^{z_i}}$$

so

$$\log(1-p_i) = -\log(1+e^{z_i})$$

Therefore:

$$\ell(\beta) = \sum_{i=1}^{n} \left[y_i\left(z_i - \log(1+e^{z_i})\right) + (1-y_i)\left(-\log(1+e^{z_i})\right)\right]$$

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Expand:

$$\ell(\beta) = \sum_{i=1}^{n} [y_i z_i - y_i \log(1 + e^{z_i}) - \log(1 + e^{z_i}) + y_i \log(1 + e^{z_i})]$$

Cancel the middle pair:

$$\ell(\beta) = \sum_{i=1}^{n} [y_i z_i - \log(1 + e^{z_i})]$$

3.1. Sources of Data within Insurance Networks

Confidential patient information generated by insurance claims is usually stored in data silos scattered across multiple business units. Claims are processed by business units involved in eligibility verification and determining benefi ts. Patient care information is processed by claims adjustment and fraud units and by business units responsible for managing innovative products such as care coordination programs and payment research units involved in studying and testing. New products such as in-house care management require designated groups to manage their constellations of patients. Other insurance companies purchase providers' electronic health record (EHR) data and naturally generate their data based on patients' hospital utilization. Substantial external data can be accessed from open data repositories that collect millions of medical records along with social determinants from a variety of sources in the insurance, health and hospital sectors. The idea is to compose the most developed and representative "model patient" in order to minimize prediction error, improving insight into that segment of the population and providing the most indicated services or treatments to these patients.

Clinical, enrollment and demographic data, per 100,000 members or patients, must therefore be reconstructed and arranged as panel datasets, which combine the people studied or analyzed at all their different time periods. For predictive model building, event-based panel datasets are in fact very powerful, as they detail the moment at which events, diagnoses, admissions or others have occurred; thus the robustness of a predictive algorithm and its verification can be much higher than using static datasets without time order of the events. The same panel datasets can also be used for descriptive analyzes and to measure in detail the accuracy of predictive models.

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Table 1. Core data foundation extracted

Data component	Examples named in the article	Why it matters for risk stratification
Demographic data	Age, gender/sex, ZIP code, census information	Baseline population structure and risk heterogeneity
Enrollment data	Coverage period, member status	Defines the observation window and denominator population
Claims/utilization data	Inpatient claims, outpatient claims, ED visits, hospital days, costs	Main signal for utilization-risk prediction
Diagnosis data	ICD-coded conditions, comorbidities	Captures disease burden and chronic-risk structure
Procedure data	CPT-coded interventions	Helps infer intensity of treatment and future care need
Pharmacy data	Medications dispensed	Adds treatment intensity and disease-management signal
Clinical/EHR data	Smoking status, family situation, clinical details	Adds depth beyond claims-only modeling
Provider/network data	Provider specialty, service level, site of care	Supports network optimization and care-routing decisions
Social determinants	Income, housing, education, employment, family context	Needed for fairness-sensitive and equity-aware prediction

4. Objective of the Study

The goal of the study is to advance predictive analytics for population health risk stratification within a large loss mitigation insurance network. The analysis fully explicates design choices underpinning the stratification process; provides machine learning and advanced analytic frameworks to define, predict, and deploy three clustering dimensions—population health risk (by utilization), expected mortality (by natural causes), and comorbidity burden; and discusses theoretical and operational significance in designing operational management for loss mitigation. The analysis emphasizes at least three aspects of risk stratification. By addressing

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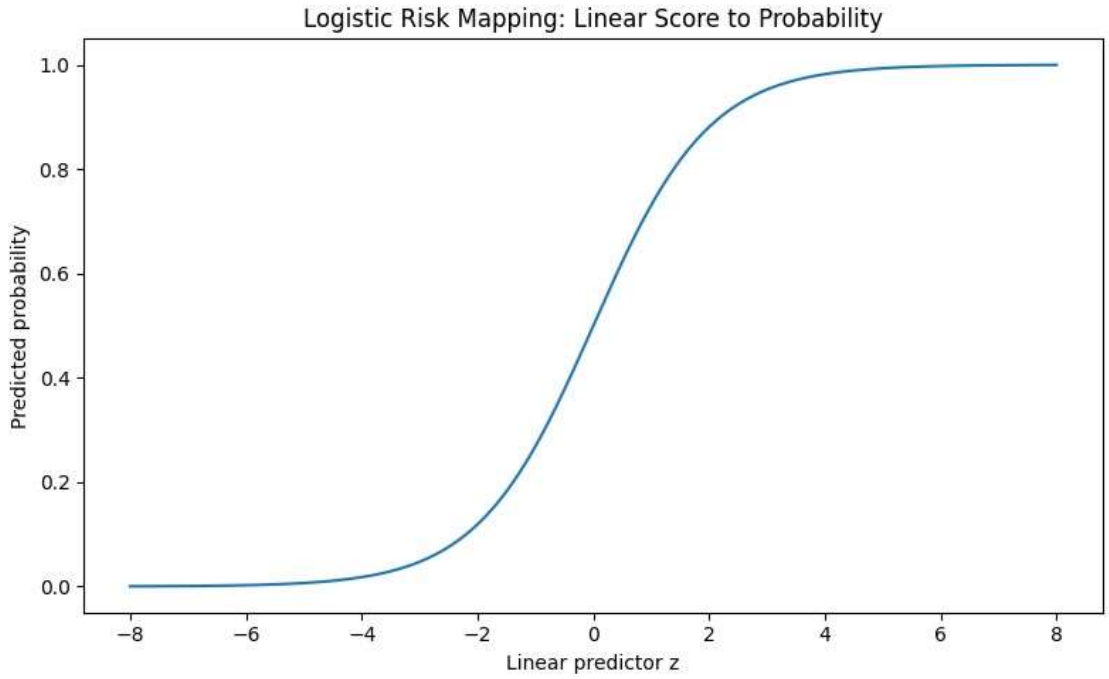
fairness and bias considerations, it advances stratification for all population segments and removes stigma associated with being classified as high risk.

Achieving success with these aims supports the wider initiative to boost loss mitigation in a large insurance network. Accordingly, demonstrable predictive performance and fairness for primary population risk segments, corroboration of results using independent datasets, and demand for predictive information as key drivers of predictive modeling in the end are vital. Clarity surrounding care management implications strengthens the justification for the broader effort of risk stratification in supporting population health.



4.1. Purpose and Goals of the Research Study

Establishing a foundation for the study entails formulating an explicit statement of the main objective and key research questions. The purpose of this research is to assess predictive performance and fairness concerning the stratification of a population of patients under the care

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VOLUME: 01 ISSUE: 01
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of a healthcare provider network offering population health management and risk-sharing contracts with insurance providers.

Three primary research questions guide the inquiry:

A. How well can a population's health risk—at the level of the individual and as defined by the concept of population health—be accurately predicted over a defined time horizon?

B. Do equity considerations and fairness constraints matter from an operational standpoint?

C. What impact, if any, does the prediction model have on operationalizing population health management? These questions translate into six measurable hypotheses, four of which pertain to predictive performance, one to fairness, and one to the practical application of the model. They are tested using a large dataset encompassing thousands of individuals and several years of utilization history. The individual risk predictions are leveraged to also assess the risk-adjusted cost of care for the population prior to the start of a risk-sharing contract.

Fig 2: Gain meaningful insights on how to optimize processes

5. Research Summary

Core components—data foundations, methodological frameworks, population health considerations, ethical concerns, practical challenges, and expected results—are briefly synthesized. Data sources, quality issues, privacy controls, and governance structures supporting stratification are identified. Contrary to conventional statistical methods, artificial intelligence techniques are foreseen as better suited for predictive tasks. Risk, acuity, comorbidity, and segmentation are defined, followed by an analysis of stratification domain, including test modules and links to preventive and therapeutic pathways. The risk-stratification framework is framed as part of an insurance-network ecosystem facilitating risk-adjusted, outcome-oriented, and equity-sensitive population-health management.

Predictive analytics for population-health risk stratification in insurance networks is a timely, topical, and very important area for insurers, providers, and patients alike. At an operational level, the development and implementation of risk-stratification systems help insurers achieve their strategic objective of optimizing risk-adjusted outcomes for the populations they serve. However, adequate predictive performance is only one aspect of their effectiveness. Predictive analytics can also support objectives of fairness, equity, and social justice if the proposed solutions are designed accordingly. Combining these four dimensions is key to helping insurers and network providers jointly fulfill their responsibility of cross-subsidization between low-risk populations and high-risk patients requiring greater resource allocation.

5.1. Core Data Components for Population Health Risk Stratification

Successful population health risk stratification demands access to data elements that provide population demographic details, historical health service utilization information, past health outcomes based on medical diagnoses and procedures performed on patients, and the impact of social determinants of health. Core data components required to implement predictive analytics for stratification of insurance network populations, focusing on risk of health loss and associated needs, include the following:

- Demographic: Age, gender, ZIP code, and census data;

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• Utilization: Health services claimed and used within specified historical periods, reported in total and by type of care, including emergency department visits and inpatient hospital days;

• Diagnoses: Past health conditions identified through the International Classification of Diseases (ICD) for establishment of comorbidities and other medical history;

• Procedures: Past health interventions reported through the Current Procedural Terminology (CPT) for identification of stratification needs and answering of life-expectancy questions;

• Social determinants: As available from external sources, covering assessment area, family, income, education, employment, and housing.

Successful use of these predictive analytics elements for population health risk stratification will ultimately depend on the precision and relevance of the data capture. Remaining success factors include maintenance of an appropriate organizational and project investment for implementation and execution, maintenance of appropriate data-security considerations, and support from both external providers and internal management.

Equation 2: From odds to odds ratio

A useful interpretation for healthcare predictors:

For a one-unit increase in x_j, holding others fixed:

$$\log\left(\frac{p'}{1-p'}\right) - \log\left(\frac{p}{1-p}\right) = \beta_j$$

Exponentiate:

$$\frac{\frac{p'}{1-p'}}{\frac{p}{1-p}} = e^{\beta_j}$$

So the **odds ratio** for one-unit increase in predictor x_j is:

$$\mathrm{OR}_j = e^{\beta_j}$$

6. Data foundations for population health risk stratification

Risk stratification for population health requires a wealth of data to inform predictions. The three essential elements are broad coverage of attributes influencing health outcomes and resource utilization (especially hospitalization), concern for data privacy and protection, and adherence to standards ensuring trustworthy data management across the stratification life cycle. These elements inform data sources, governance, quality management, privacy, and access controls.

The foundation for the estimation resides naturally within insurance networks. Together, enrollment data, claims data, clinical data (often EHRs), and network provider data constitute the four key pillars supporting such initiatives. Enrollment data provide the demographic scaffolding essential for any stratification, while claims data, integrating utilization and diagnosis, serve as the primary source for outcome prediction. These two data sets constitute the broadest record within the network, available for any member and any observable condition regardless of service location. Clinical data add an important depth of information for those with predicting risk and acuity, especially at later stages such as serious morbidity and dying. Network provider data enhance the predictive value of stratification for care-level interventions, furnishing information on the variations in specialty type and service delivery level driving care cost and demand patterns.

6.1. Data sources within insurance networks

Predictive Analytics for Population Health Risk Stratification in Insurance Networks

The data foundations for risk stratification encompass sources, governance, quality, privacy, and access controls. Within a commercial insurance network, primary data originate from policyholder databases, claims, enrollment, and premium collections. Claims datasets capture diagnostic, procedural, and financial details (e.g., provider, location, coverage, adjustments) for separate inpatient and outpatient services, while pharmacy claims include details on medications dispensed. Enrollment data document the period of coverage for each policyholder. Policyholder demographics (age, sex, and ZIP code) and premium data provide characteristics of the population.

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Data from multiple but disparate sources are largely complementary yet differ in quality and coverage. Enrollment data ensure a complete view of people during their entire period of coverage. Claims data provide details that are missing from enrollment, such as information defining network-funded services. Risk-adjusted outcomes combine utilization, outcome, and adjustment data from claims and enrollment data. Electronic health records deliver additional clinical and patient-reported information on country of origin, smoking status, family situation, and therapeutic alliances—including social determinant factors.

Data governance structures address privacy concerns arising from population health analytics and predictive modelling by establishing trusted third-party mechanisms for the anonymization, aggregation, and release of individual prediction results in accordance with the Health Insurance Portability and Accountability Act. These governance frameworks also enable the fulfilment of Health Information Technology for Economic and Clinical Health Act requirements pertaining to the use of health information for measures, research, public health, and health care operations for the benefit of the population. Requirements stemming from the United States Food and Drug Administration's Cybersecurity Guidance for Networked Medical Devices Containing Off-the-Shelf Software are further satisfied through access control policies and procedures for information systems that contain or use personal health information.

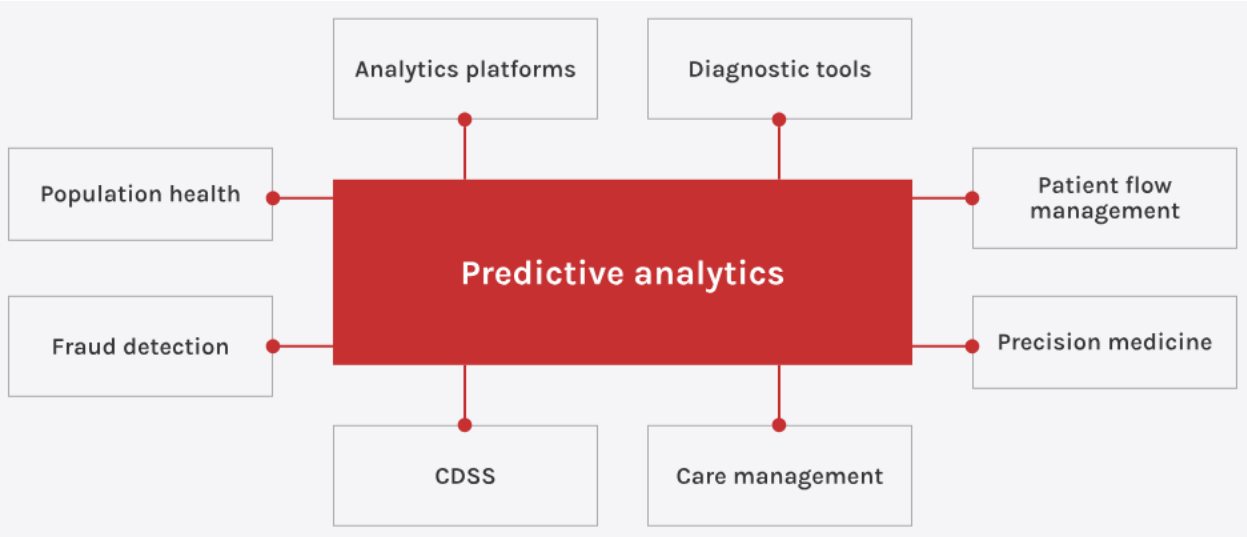

Fig 3: Predictive analytics solutions

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VOLUME: 01 ISSUE: 01
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6.2. Data quality, privacy, and governance

Five key data quality attributes—completeness, consistency, accuracy, timeliness—affect predictive model performance. External datasets, though not assigned a direct quality score, enhance the breadth and effectiveness of models. Privacy protections safeguard sensitive data against unauthorized access.

Network health risk stratification relies on a data ecosystem governed by a framework for quality management, access control, and compliance with privacy and security regulations. Such a framework ensures the quality and fidelity of data from different sources, including claims, enrollment files, electronic health records, provider data, and risk-related elements drawn from external repositories.

Regulatory bodies impose conditions for the ethical use of individuals' health and personal information for analytical applications. Thus, governance structures should establish oversight of algorithmic systems programmed to render automated decisions about the individuals' future health outcomes and needs. These decisions often carry practical implications for the individuals, such as difference in insurance premium, exclusion from a provider network, an increased chance of being assigned to a provider with fewer resources, or an increased risk of being flagged as the primary focus of a costly care coordination process.

Table 2. Modeling methods

Method	Outcome type	Main idea	Strength	Limitation
Logistic regression	Binary event prediction	Models probability of an event from predictors	Interpretable, standard baseline	Limited nonlinearity unless engineered
Cox proportional hazards	Time-to-event prediction	Models hazard over time using covariates	Uses event timing	Assumes proportional hazards
Random forest	Classification / risk ranking	Ensemble of trees averaged together	Handles nonlinearities and interactions	Less transparent

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Method	Outcome type	Main idea	Strength	Limitation
Gradient boosting / boosted trees	Classification / risk ranking	Sequentially improves errors from prior learners	Strong predictive performance	More tuning needed
Neural networks	Complex nonlinear prediction	Learns layered nonlinear mappings	Flexible with rich data	Lower interpretability
Nested / group cross-validation	Validation strategy	Honest performance estimation	Reduces optimistic bias	Computationally heavier

7. Methodological frameworks for risk stratification

Mainstream statistical methods for predictive modelling, primarily logistic regression and the Cox proportional hazards model, are well understood and widely used throughout the academic and professional literature. Their strengths and weaknesses are also well known. These methods can often be used to advantage, especially when data availability is limited. But care is needed in the choice of predictor variables to ensure that important nonlinear relationships, multicollinearity, and variable interaction effects are properly addressed. When sufficient high-quality historical data are available, machine learning techniques such as ensemble methods (for example, random forests, gradient boosting, catboost) and neural networks (multi-layer perceptrons, recurrent networks) usually reduce prediction errors. Proven validation approaches such as nested cross-validation and group-cross-validation ensure honest performance estimation for supervised predictions, while evaluation on an unseen independent dataset verifies model transportability.

Novel and advanced analytics, especially those based on large language models, are also becoming important drivers of innovation. Their rapid evolution is simultaneously exciting and daunting: new methods, jargon, benchmarks, and open-source implementations appear every few months. But few have stood the test of time, and classic methods (such as logistic regression, survival analysis, and survival curves) still play an essential role in the risk-stratification art and science. In deciding which method to use, the balance between predictive performance and interpretability dictates whether the most sophisticated machine-learning tools or simpler

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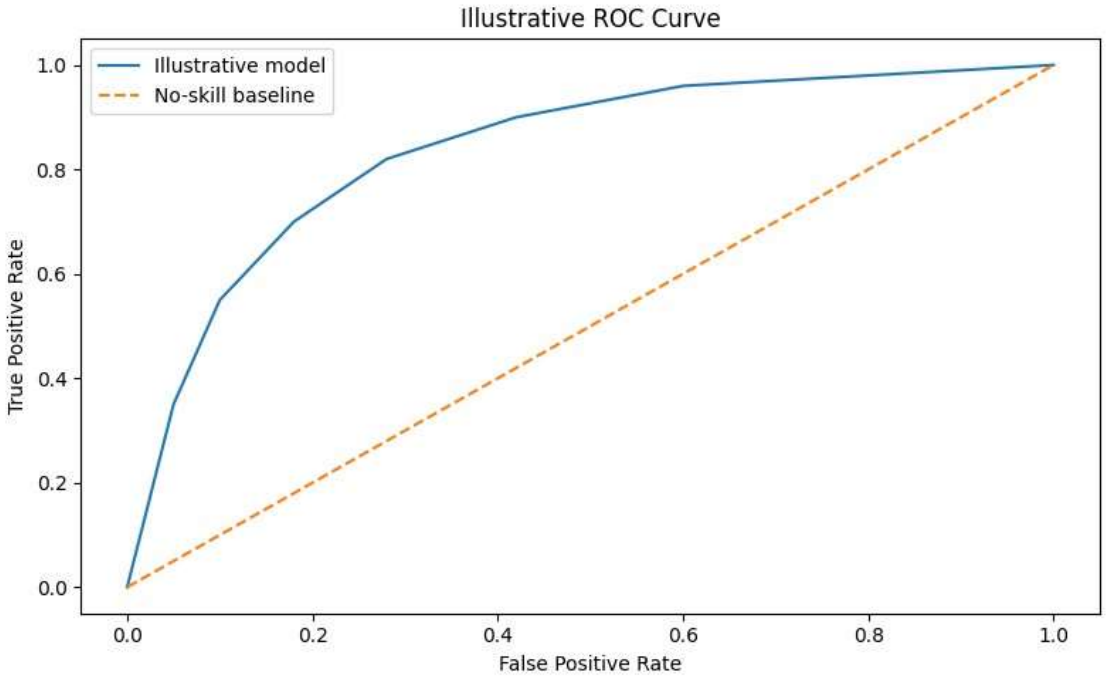
statistical approaches are the best choice for any given prediction task. Employing both in a complementary manner is often best.



7.1. Traditional statistical approaches

Predictive Population Health Risk Stratification Development

The prevailing practice of analyzing healthcare utilization data through traditional statistical methods such as logistic regression, survival analysis, and survival curves is well established. Although these approaches can yield valuable insights into the area of interest, some standard challenges limit their effectiveness to predict or appropriately stratify population healthcare needs. One major limitation is that the underlying temporal aspect of healthcare utilization is not accounted for, making it difficult to accurately model utilization over the entire follow-up period. Additionally, the parameter estimates cannot directly provide additional information that could be useful for care management. For instance, in the logistic regression setting, the probability being estimated can sometimes be skewed within certain population

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groups. These challenges and many others are prompting healthcare organizations, researchers, and predictive modellers to explore the potential suitability of applying modern machine-learning and advanced-analytical methodologies on healthcare utilization data.

The healthcare literature elucidates numerous machine-learning and artificial-intelligence methodologies being employed to predict various healthcare utilization outcomes. Ensemble methods (like bagging, boosting and Random Forest), Gradient Boosting Machines, and Neural Networks are attracting substantial attention of late. A review of these methods emphasizes their ability to provide predictions for various strata (especially high-volume categories) with relatively favourable classification accuracy. Internally, various machine-learning and artificial-intelligence-based predictive models are being developed and tested, with optimal model selection performed through an extensive array of model-optimization and selection-supporting activities.

7.2. Machine learning and advanced analytics

Classic statistics offers important and oft-used methods for predictive modeling, such as logistic regression (for binary classification), survival analysis (in time-to-event settings) and calculation of survival curves. Such models can produce good predictive performance and serve as interpretable summaries of risk. Yet they are limited in their flexibility, and so ensemble methods capable of learning higher-dimensional and non-linear relationships from data have become dominant.

Gradient boosting, pioneered within the AdaBoost algorithm (Freund & Schapire 1997), involves training a sequence of models (not necessarily trees) so that each subsequent model attempts to learn the training errors made by the previous models. More specifically, training proceeds as follows. Samples are weighted according to prediction error, with more emphasis on the samples that were previously mispredicted, and a new model is fit to the data with these weights. The predictions of all models are then combined by a weighted sum. Later iterations can adjust or even cancel the contributions of earlier ones.

Despite its popularity, the AdaBoost algorithm is limited to binary outcomes and categorical predictors. It can be extended to allow categorical predictors to take on more than two values, but a more powerful alternative is to combine the predictive power of random forests with boosting. In gradient-boosted trees (Friedman 2001), all models are decision trees. The overall prediction is an additive combination of the predictions from all trees, but each tree is fit

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AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

using the negative gradient of the loss function (which does not have to be restricted to the 0–1 loss) with respect to the current prediction.

8. Population health concepts informing risk stratification

Population health risk stratification is concerned with predicting adverse health events of different types (deaths, hospitalizations, emergency department (ED) visits, complications) that can vary in severity, prognosis, and cost, and that reflect different dimensions of health and well-being. Three population health concepts are key to risk stratification: risk, acuity, and comorbidity. Risk stratification identifies patients at high risk of a specific type of event. Acuity stratification categorizes patients based on the severity of predicted events. Comorbidity stratification classifies patients who are likely to experience a combination of events. Patients are then assigned to predictive groups.

Multiple population health segmentation schemes exist, including clusters, population health pathways (PHPs), and care-level categories. Care management interventions are typically tailored based on these segmentation groups. Stratification of insurance networks is enhanced by clarifying and defining these concepts and consequences. These elements may be applied when stratifying the full population health continuum, complemented by concepts of social vulnerability and health equity. A more expansive definition of population health would therefore include these two dimensions. Ultimately, the risk stratification is using predictive models to assign patients to population health pathways (PHPs), defined according to the predicted risk and acuity of multiple outcome events.

Equation 3: Cox proportional hazards model

The names the **Cox proportional hazards model** and survival analysis.

Let:

- T = time to event
- $h(t \mid x)$ = hazard at time t given covariates x
- $h_0(t)$ = baseline hazard

The Cox model is:

$$h(t \mid x) = h_0(t)e^{\beta^\top x}$$

Why "proportional hazards"?

Take two patients a and b with covariates x_a and x_b:

$h(t \mid x_a) = h_0(t)e^{\beta^\top x_a}$ $h(t \mid x_b) = h_0(t)e^{\beta^\top x_b}$

Form the ratio:

$$\frac{h(t \mid x_a)}{h(t \mid x_b)} = \frac{h_0(t)e^{\beta^\top x_a}}{h_0(t)e^{\beta^\top x_b}}$$

Cancel $h_0(t)$:

$$\frac{h(t \mid x_a)}{h(t \mid x_b)} = e^{\beta^\top (x_a - x_b)}$$

This ratio does **not depend on** t, which is why hazards are proportional.

Derive survival function from hazard

By definition,

$$h(t) = \frac{f(t)}{S(t)}$$

and cumulative hazard is

$$H(t) = \int_0^t h\,(u)\,du$$

The survival function satisfies:

$$S(t) = e^{-H(t)}$$

For Cox:

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
ISSN: 3067-1140
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

$$H(t \mid x) = \int_0^t h_0(u) e^{\beta^\top x} \, du$$

Since $e^{\beta^\top x}$ does not depend on u,

$$H(t \mid x) = e^{\beta^\top x} \int_0^t h_0(u) \, du$$

Define baseline cumulative hazard:

$$H_0(t) = \int_0^t h_0(u) \, du$$

Hence:

$$H(t \mid x) = e^{\beta^\top x} H_0(t)$$

Now substitute into survival:

$$S(t \mid x) = e^{-H(t|x)} = e^{-e^{\beta^\top x} H_0(t)}$$

Because $S_0(t) = e^{-H_0(t)}$,

$$S(t \mid x) = \left(S_0(t)\right)^{e^{\beta^\top x}}$$

8.1. Definitions of risk, acuity, and comorbidity

Accurate definitions of risk, acuity, and comorbidity underpin appropriate stratification and intervention in predictive population health risk management. Risk may be relatively straightforward to define, in a clinical implications context, using either the probability of a specific adverse outcome, such as death, or the expected cost of future medical care over a specified time horizon. However, neither risk model may be value-neutral. The former may focus management resources disproportionately on at-risk but potentially healthy individuals, while the latter takes no account of the differential intensity of care management resources. The notion of acuity encompasses both volume and intensity, being generally accepted as a measure of illness

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

severity within a multi-condition setting. Acuity may also be explicitly modelled over time for prediction chores.

Predictive population health risk stratification and care management decisions typically consider both the level of risk faced by individuals and their historical health consumption (i.e., a measure of acuity) across some defined intervals considered relevant in planning care management resource allocation and design. The standard approach has been to define three segmentation categories—such as low-risk, rising-risk, and high-risk—that correspond to the likelihood of cost escalations (probability of future costs exceeding a specific level) and the volume of such escalations, based on conventional predictive model outputs. However, defining care management resource allocation across a broader range of predictive strata may provide resources to individuals in both low-risk and high-risk strata where specific resource allocation for addressing the expected future needs is likely to add both clinical and economic value. It may also be more valuable for care management resource allocation intensities to be a function of comorbidity rather than of risk or predictive-volume stratification categories.

Fig 4: Risk Stratification Benefits

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

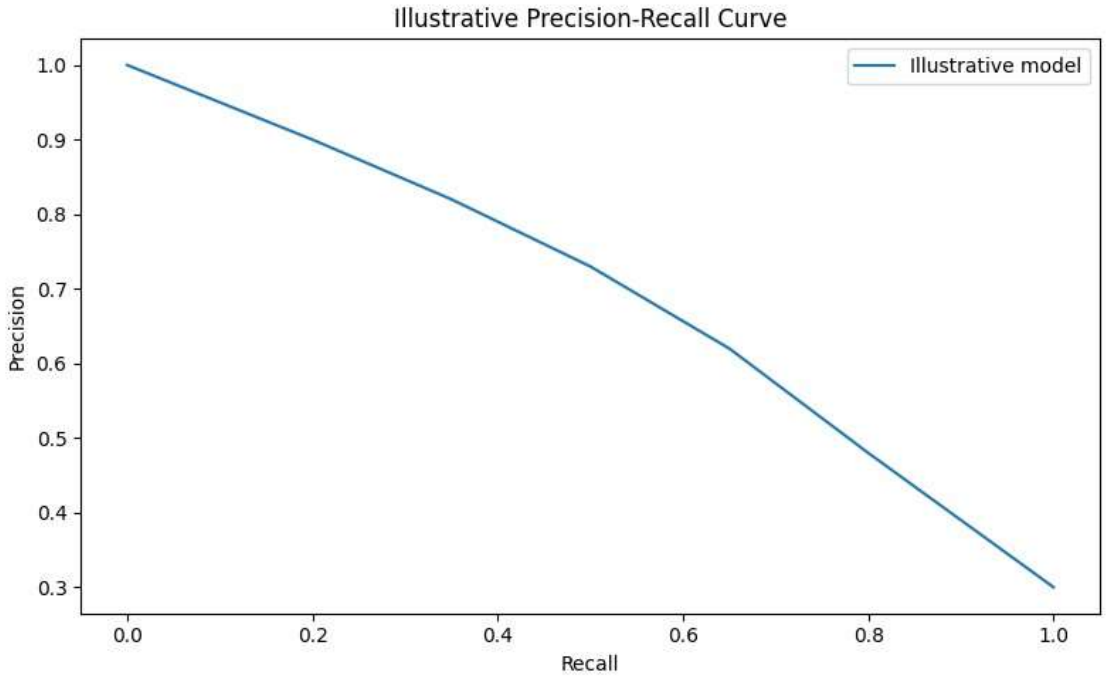
8.2. Segmentation schemes and their implications for care management

Risk levels influence resource allocation, care process design, and supervision requirements. Yet intervention design cannot rely solely on risk levels; substantial variation in outcomes and costs exists within high-risk strata. Recognizing subgroups with shared characteristics can enhance understanding and intervention design, as achieved with hypertension and diabetes proxy risk groups. Analyses using care process data might identify Groups at Risk (GARI) or "prepare-and-predict" pathways. General and Acute Peak (GAP) analysis delineates care and cost drivers for subpopulations at varying demand peaks.

These segmentation analyses illuminate Primary Health Problems (PHPs), indicating patients' predominant nor pathological or health problem types (such as respiratory, digestive, or metabolic) warranting specific predictive intervention design. Interpretative frameworks explore interventions and activities associated with Patient Cost Potential (PCP) or mean costs across clusters. Care-Level Categories (CLC) group patients by care-level demand patterns, revealing shared characteristics, acute demand drivers, and comorbidity correlations.

Clustering identifies illness clusters within high-risk populations for GBD analysis. Clusters inhabit high-cost, high-risk parts of power laws; partitioning methods are unsatisfactory. Portrait clusters reveal typical patients, and cost levels of cluster representatives can guide interventions. K-outliers delineate high-cost-outlier groups.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08



9. Implementation within insurance networks

Integration of predictive analytics into health insurance networks enables early identification of individuals at risk for preventable, serious health events. Directing high-impact interventions toward these individuals can facilitate prevention at the lowest possible cost. Implementation in a health insurance network involves integration into care management workflows, along with processes that support provider engagement and allocate resources throughout the network.

Care management departments execute risk stratification, using the results to guide outreach and interventions. Initial engagement with high-risk segments is prioritized, focusing on the delivery of timely and appropriate programs and services to avert high-acuity and high-cost events. Start and stop triggers monitor the efficacy of these interventions, ensuring that patients remain within the specified population segments that warrant the intervention. Results that indicate a positive response lead to additional resources being devoted to the intervention, while indications of no response result in the application of alternative programs. When predictable

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
ISSN: 3067-1140
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

shifts occur in high-risk segments, these results are reported to providers. The stratification products can also support network design by identifying the segments that incur the greatest risk-adjusted expenditures and guiding the deployment of resources to counteract the risk.

As care pathways span across multiple providers, health plans can analyze the segments that introduce the greatest resource demand or risk-adjusted resource demand. Based on the magnitude of that demand, combined with the available network resources, care pathways can be consolidated around specific providers or organizations. The direction of travel taken by the different segments can also facilitate the identification of the network providers best placed to manage that demand and avert high-acuity and high-cost events.

Table 3. Evaluation metrics

Metric	Formula idea	Interpretation
ROC curve / AUROC	TPR vs FPR across thresholds	Discrimination ability across thresholds
Precision	TP / (TP + FP)	Among predicted high-risk, how many are truly high-risk
Recall	TP / (TP + FN)	Among true high-risk, how many are found
F1 score	Harmonic mean of precision and recall	Balances missed cases and false alarms
AUPRC	Area under precision–recall curve	Useful for imbalanced event prediction
MCC	Correlation-style summary from TP, TN, FP, FN	Balanced metric even with class imbalance

9.1. Integrating risk stratification into care management workflows

Risk stratification informs the allocation of operating resources, identification of natural partners within the network, and coordination of direct care efforts directed at especially vulnerable population subgroups. For the first two roles, stratification facilitates a shift from relying on volumes of services or payer revenues to predicting and planning for the mix of

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

patient needs that will translate into revenues—as well as creating payer-provider partnerships in which each side can play to its institutional strengths. Resource-intensive analytic models predict near-term hospital admissions, while more qualitative assessments identify groups of patients likely to require substantial non-acute post-acute, or community-based support. Hence, the provider network components that can best support those groups are made apparent, helping to avoid the tendency for services to evolve in silos that lack the full complement of necessary specialties and functional capabilities. Finally, external factors such as climate-driven health risks, social upheavals, and emerging diseases create new areas of patient vulnerability that require timely responses from the healthcare ecosystem as a whole.

Coordination of care-capable resources around the needs of these specific population segments reduces the likelihood of adverse event clusters becoming major performance outliers. For example, when municipal flooding threatens a ZIP code region, preventive information can be directed to the affected patient community and local crisis intervention services readied for timely response. Such coordination requires integrating care management with stratification in a closed-loop workflow that generates reminders when newly diagnosed patients enter risk categories at elevated care levels, and these reminders are shared with care managers who oversee and execute direct services or mobilize the resources of specialty care, post-acute location services, and community health partners.

9.2. Resource allocation and network optimization

Population health risk stratification has important implications for resource allocation in provider networks. Results from the predictive models and associated care pathways can inform the optimal distribution of limited clinical, administrative, and operational resources both across provider systems and within a single provider system, depending on the local disease burden and other conditions. Risk stratification can also enable an insurance plan to replicate the resource investments in provider networks that have improved risk-adjusted outcomes, thereby supporting value-based reimbursement models. Furthermore, a predictive approach helps mitigate the risk of lower-quality outcomes resulting from network expansion by ensuring that adequate resources are made available to care for additional patients and by facilitating patient flow through the network. Local providers can use risk stratification to bring appropriate interventions to bear on patients and populations in order to improve outcomes, increase value, and manage costs.

Resource allocation decisions focus not only on the adequacy of resources for the indicated care pathways, but also on the establishment of a balanced network of clinical

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

providers to facilitate timely and appropriate care for patients at all levels of acuity, with diverse social and demographic characteristics. A balanced network is required to deliver effective care to the higher-acuity and multi-morbidity patients who account for a disproportionate share of total costs and for substantial shares of chronic disease costs, endpoints such as admissions, and preventable and avoidable costs. Risk stratification therefore provides a valuable tool for managing provider network design across these dimensions.

10. Ethical, legal, and regulatory considerations

Fairness, privacy, and accountability are paramount. Predictive models for stratification, care intervention, and risk-adjusted outcome improvement must not unfairly disadvantage members of any group. Bias and other fairness issues are commonly investigated, with mitigation and corrective steps employed as appropriate. Privacy is supported by a process that enables members to understand how their personal data is used, including the ability to opt out without impacting their care. Data security and adequate consent processes provide confidence throughout the network. Relevant regulations are adequately addressed.

Bias, fairness, and equity in predictive models are serious issues and should be addressed proactively. Core predictor variables such as age, sex, and race/ethnicity are well-documented determinants of health. While commonly included in models, they nevertheless contribute to disparate outcomes, appear unjust, and should be treated cautiously. Other sources of bias also exist. For example, racial and socioeconomic inequities in access to healthcare services or social determinants may correlate with predictive features that increase risk but do not account for underlying need. Issues of fairness and equity must therefore be considered when interpreting the results.

Whistles and other external safeguards also help alleviate bias, fairness, accountability, and ethical issues. Continuous model monitoring is critical to ensure their predictive capabilities remain current as population behavior changes over time. Accuracy, bias, and fairness analyses also play an important role in sustaining performance development efforts. Further approaches, including the implementation of a fairness fence, can help address fairness-related concerns. Effectively, any such undertakings provide networks with documentation that predictive models have been built responsibly, understood before use by the relevant stakeholders, and are currently functioning accurately. Data privacy, security, and legal compliance issues are also essential. Predictive models rely on the sharing of personally identifiable data, including medical encounters and social determinants.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

Robust internal and external data security and privacy processes are therefore critical to ensure personal data are appropriately safeguarded. Consent is included as part of routine disclosures; however, members remain free to opt out of sharing their personal data at any stage without impacting the care services they receive. Failure to consult the prediction models when making care decisions may limit effectiveness, return on investment, and risk-adjusted outcomes throughout the insurance or care network. Nevertheless, consent remains a fundamental part of any network-wide adoption of predictive risk stratification modeling.

Equation 4: Precision, recall, and F1 score

Let:

- TP = true positives
- FP = false positives
- FN = false negatives
- TN = true negatives

Precision

$$\text{Precision} = \frac{TP}{TP + FP}$$

Interpretation: of all patients predicted high-risk, what fraction truly are high-risk?

Recall

$$\text{Recall} = \frac{TP}{TP + FN}$$

Interpretation: of all truly high-risk patients, what fraction did the model identify?

Derive F1 from precision and recall

The F1 score is the harmonic mean of precision P and recall R:

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

$$F_1 = \frac{2PR}{P+R}$$

Now substitute

$$P = \frac{TP}{TP+FP}, \qquad R = \frac{TP}{TP+FN}$$

Then

$$F_1 = \frac{2\left(\frac{TP}{TP+FP}\right)\left(\frac{TP}{TP+FN}\right)}{\frac{TP}{TP+FP}+\frac{TP}{TP+FN}}$$

Step 1: Simplify numerator

$$2\left(\frac{TP}{TP+FP}\right)\left(\frac{TP}{TP+FN}\right) = \frac{2TP^2}{(TP+FP)(TP+FN)}$$

Step 2: Simplify denominator

$$\frac{TP}{TP+FP}+\frac{TP}{TP+FN} = \frac{TP(TP+FN)+TP(TP+FP)}{(TP+FP)(TP+FN)} = \frac{TP[(TP+FN)+(TP+FP)]}{(TP+FP)(TP+FN)} = \frac{TP(2TP+FP+FN)}{(TP+FP)(TP+FN)}$$

Step 3: Divide numerator by denominator

$$F_1 = \frac{\frac{2TP^2}{(TP+FP)(TP+FN)}}{\frac{TP(2TP+FP+FN)}{(TP+FP)(TP+FN)}}$$

Cancel the common denominator:

$$F_1 = \frac{2TP^2}{TP(2TP+FP+FN)}$$

Cancel TP:

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

$$F_1 = \frac{2TP}{2TP + FP + FN}$$

So the fully reduced F1 formula is:

$$F_1 = \frac{2TP}{2TP + FP + FN}$$

10.1. Fairness, bias, and equity in predictive models

Care disparities exist across populations defined by race, ethnicity, and religion. Such variables are also often associated with changes in results. Thus, care produced or managed for such populations needs to be analyzed systematically. Providers could be held accountable for differences between expected and actual outcomes based not on overall network results but on population-specific results. Failure to do so can lead to bias in models used, which can be evident when a population group is concentrated in a small number of cases.

Transparent explanations of how predicted results are generated are crucial in this area. Predictive models can be biased and lead to unfair results against protected groups. As a result, bias detection tests can be applied to estimate whether a model is biased against a group, in which case hiding the group indicator can relieve or reduce the group bias of the model, albeit with a potential loss in overall prediction accuracy. Changing a model is possible in specific use cases and is even a legal requirement in some countries. Fairness-enhancing interventions can mitigate these concerns, and ML offers various methods of achieving such fairness. The ultimate goal remains to avoid allocating or denying resources solely due to suggestive sensitive attributes.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

Fig 5: Predictive Analytics in Healthcare

10.2. Privacy, consent, and data security

The implementation of any predictive solution relies on the availability of data to train the model and ensure that the attributes being predicted can be generalizable across populations and settings. Privacy regulations also govern the use of such data. Members of a population have different levels of comfort regarding how their data may be used. There is also a social contract which allows for the data for public health, audit, research, and quality control. All these areas are trying to gain consent and justification for the use of data in a transparent manner. The primary fact that needs to be ensured in the data is that it must be treated in a security-protected manner so that unauthorized access is denied. This access is usually given to authorized personnel only.

Care must be taken to follow the data classification guidelines relevant for the country the data belongs to. For such projects that may be deploying predictive models, it may involve training and re-training the model, sharing the interim results to know if models are on the correct track, translating the model back to rules for final consideration or if not agree to know why it failed in that population. Hence, they get treated at a lower risk zone compared to the

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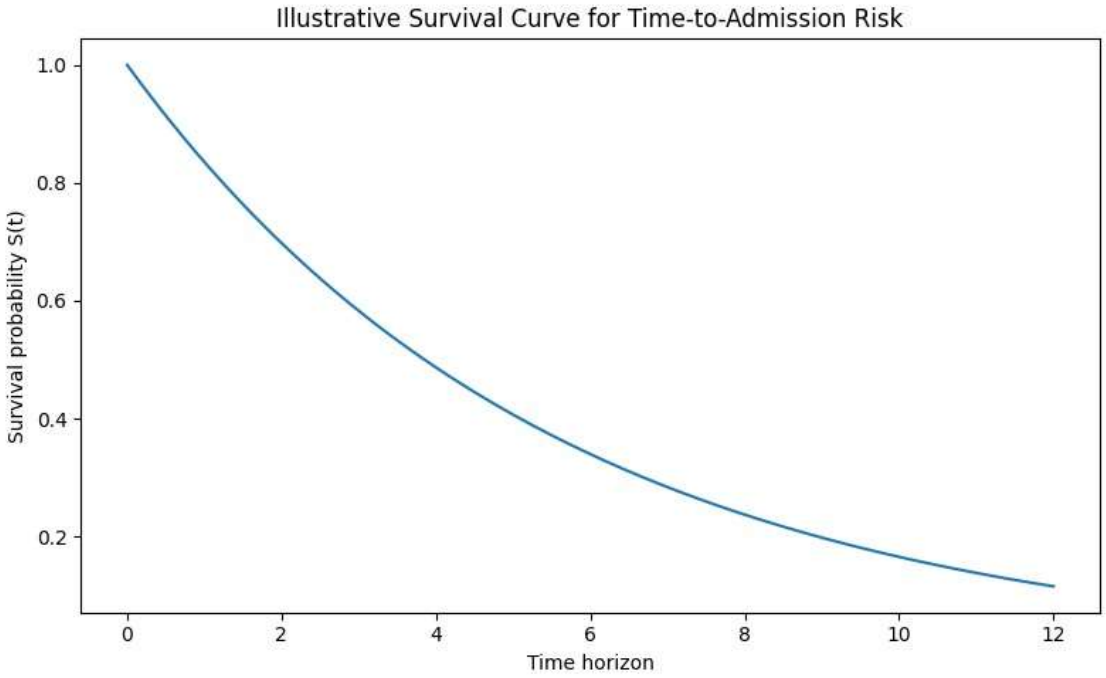
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

model pipeline that goes through only once. The usage of model prediction outcomes must also be carefully documented to ensure that it does not lead to negative repercussions on any of the members residing in that population. Final decisions must always be taken based on the actual data residing with the end users.



11. Practical challenges and risk management

A range of practical challenges could impede the implementation of predictive models for population health risk stratification at scale, including data silos within organizations, insufficient agreement among partners on sharing data across organizations, resource constraints for model development and deployment, and trustworthiness of the resulting predictions. The analysis also needs to consider potential mitigation strategies for possible risks that arise in deployment. Some of these risk factors have already been tackled, while supporting strategies will be addressed in the following sections.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 09

Data from different parts of the insurance networks reside at different organizations and in different silos. In many situations, due to concerns of privacy and security of sensitive information, data is not made available outside the organization that collected it. Organizations that serve multiple insurance payer organizations face multiple data sets with often conflicting definitions of similar information. These issues need strategies to support the elimination of silos, especially for the areas of social determinants of health, housing, food insecurity, mental health, and substance abuse, which are often stored in different repositories.

Carefully assessing risk stratification and the predictive models behind it can avoid causing more harm than good. Machines, algorithms, and artificial intelligence are usually tagged as being biased or unfair. Whether true or not, all these terms are very delicate to any process where humans factor into the outcome—because AI is often seen as a metaphor of God, and humans are afraid of having God miserable, humans work very hard to avoid bias, fairness, or any other issue behind AI,—the result is that predictive models deployed for risk stratification and resource deployment must be carefully examined."

11.1. Data silos and interoperability

Silos of clinical and claims records across public and private systems reduce the population-level predictive potential of insurance networks. The internal depth and richness of a network's data is attractive for predictive modelling. Yet privacy concerns, and variable incentive structures among parts of the system, force some healthcare and support activities to External Partners. These partners also contain clinical and claims records of their own population cohorts, but without the intentional design of the insurance-network approach. For major External Partners, the data records weigh in at millions of individuals but are not fully utilized for predictive modelling due to demographic and integrative limitations.

Internet-based government programs serve the very old, handicapped, destitute and badly afflicted. Their claims records function well for descriptive purposes but lack temporal homogeneity due to frequent prescribed dependency on other care levels. Union contracts negotiate direct healthcare with healthcare establishments in all major metropolitan areas, thereby enabling Internal Partner Predictive Model indirect development. One non-interactive model-group served Union care-layer needs. More development occurred via available Hospital-level predictive modelling.

11.2. Generalizability and transportability across populations

Generalizing a predictive model to a new, yet similar, population is commonly referred to as transportability; it has implications for population health risk stratification as well. In this context, it is assessed whether the predictive patterns observed in the training Medicare population hold for the newly deployed Medicare population and, most importantly, for the deployed commercial population.

A few preliminary steps can verify the plausibility of such an assessment. First, the populations can be compared to examine the extent of their similarities and differences. Second, the available clinical data—namely, individuals' prior-year diagnoses and procedures—and associated risk status can also be examined for alignment. Third, the stability of the model outputs in predicting current-year risk status can be tested using the training Medicare data. Such tests provide supportive evidence, warranting a more formal analysis of transportability.

Equation 5: Matthews correlation coefficient (MCC)

Also named directly in the paper.

MCC is:

$$\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Why this form?

It is the Pearson correlation between:

- actual labels $Y \in \{0,1\}$
- predicted labels $\hat{Y} \in \{0,1\}$

For binary classification, expanding the correlation in terms of contingency-table counts yields the formula above.

Step-by-step mapping of terms

- $TP \cdot TN$: agreement on positives and negatives

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 09

- $FP \cdot FN$: disagreement penalty
- denominator: normalization by all four marginal totals

So MCC:

- $= 1$ perfect prediction
- $= 0$ no better than random pattern correlation
- $= -1$ total inverse prediction

12. Results

Performance metrics shape the analysis of predictive performance, fairness, and operational impact of risk stratification for care management or network contracting. Core elements encompass data requirements, accuracy and fairness of models employed to build stratification schemes, and the consequences of introducing and applying such structures. Predictive performance considers ACLD divergence, with increasing deviation flagging greater misallocation of earlyPs to late status. Support for care management hinges on improved ADMs within risk-adjusted covariates for direct costs and hospital admissions or readmissions.

Building EHR or claims-based predictive models responding to the input sets described delivers adequate discrimination of these strata. Consideration of fairness addresses compositional disparities, as stratification schemes that directly support care management—through depth of funding, allocation of dedicated resources, or special means—are correctly mapped largely along social differences rather than on need. Testing of population health (PHP) categories reveals a systematic tendency to label minor or non-acute patients as early or late; further analysis of acute and early APC explodes the effects of adding surgery within 30 days or not achieving the intended proposed outcome.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
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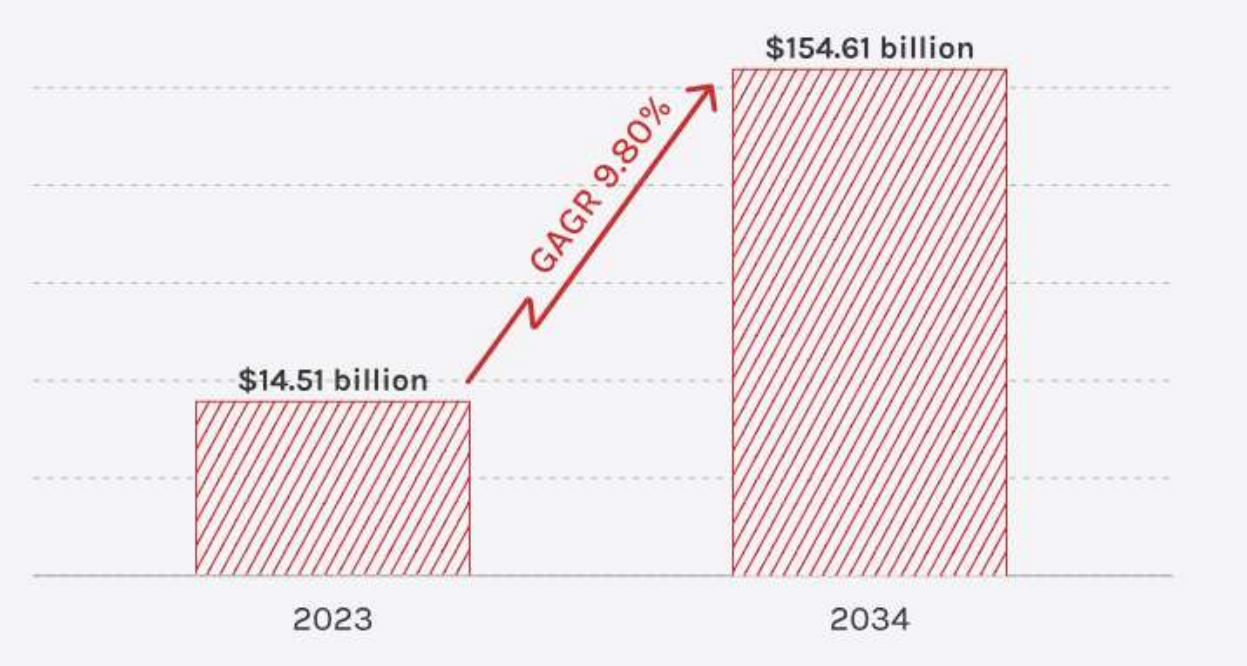

Fig 6: Healthcare predictive analytics market size

13. Conclusion

Data, governance, and strategic considerations frame five main components of risk stratification for care management in insurance networks: A data-driven strategy for care management candidates uses historical, cross-sectional enrollment and claims, diagnoses and procedures, and ideally supports characteristics of the population served and the decisions made by organizations. Predictive models for key segments of the population factor in health determinant data. Stratification is incorporated into workflows for care coordination and patient engagement. Combined, these components help manage quality and utilization, support the design of provider networks, and ensure that care programs are targeted to the population segments expected to benefit. Addressing biases in the stratification algorithms and protecting the privacy of individuals receiving predictive care management are also important considerations.

The research identifies the main constituents and relationships for the predictive analytics of population-needs stratification, an application of advanced machine learning and analytic methodologies focused on insurance, and proposes a data-driven framework for supporting population health using advanced predictive modeling. These components and their interactions inform the development of predictive models for use in insurance networks. The analysis and its implications are grounded in practice; the objective is to clarify a clearly delineated area of action and its core constituents.

References

1. Abdulazeem, H., Whitelaw, S., Schauberger, G., & Klug, S. J. (2023). A systematic review of clinical health conditions predicted by machine learning diagnostic and prognostic models trained or validated using real-world primary health care data. PLOS ONE, 18(9), e0274276.
2. Coran, J. J., Schario, M. E., & Pronovost, P. J. (2022). Stratifying for value: An updated population health risk stratification approach. Population Health Management, 25(1), 91–99.
3. Kolla, S. K. (2023). Learning Health Systems Machine Intelligence for Clinical Prediction and Healthcare Optimization. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 6(2), 7955-7966.
4. Evans, L., Wu, Y., Xi, W., Ghosh, A. K., Kim, M.-H., Alexopoulos, G. S., Pathak, J., & Banerjee, S. (2023). Risk stratification models for predicting preventable hospitalization in commercially insured late middle-aged adults with depression. BMC Health Services Research, 23, 621.
5. Kaushik, K., Bhardwaj, A., Dwivedi, A. D., & Singh, R. (2022). Machine learning-based regression framework to predict health insurance premiums. International Journal of Environmental Research and Public Health, 19(13), 7898.
6. Klein, P. P. F., van Kleef, R., Henriquez, J., & Paolucci, F. (2023). The interplay between risk adjustment and risk rating in voluntary health insurance. Journal of Risk and Insurance, 90(1), 59–91.
7. Aitha, A. R. (2023). Cloud-Native Big Data AI/ML Framework for Risk Intelligence and Fraud Control in Banking and Insurance Ecosystems. Available at SSRN 6157967.
8. Maxwell, J. M., Russell, R. A., Wu, H. M., Sharapova, N., Banthorpe, P., O'Reilly, P. F., & Lewis, C. M. (2021). Multifactorial disorders and polygenic risk scores: Predicting common diseases and the possibility of adverse selection in life and protection insurance. Annals of Actuarial Science, 15(3), 488–503.

9. Mourmouris, J., & Poufinas, T. (2023). Multi-criteria decision-making methods applied in health-insurance underwriting. Journal of Decision Systems, 32(1), 52–84.
10. Mattaparthi, R. (2023). Connected Fleet Intelligence: Edge-Centric Analytics and Computer Vision for Predictive Manufacturing and Asset Resilience. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 6(5), 9077-9088.
11. Sperrin, M., Martin, G. P., Sisk, R., et al. (2021). Informative presence and observation in routine health data: A review of methodology for clinical risk prediction. Journal of the American Medical Informatics Association, 28(1), 155–166.
12. Raza, M. M., Venkatesh, K. P., & Kvedar, J. C. (2022). Intelligent risk prediction in public health using wearable device data. NPJ Digital Medicine, 5, Article 176.
13. Kshirsagar, R., Hsu, L.-Y., Chaturvedi, V., Greenberg, C. H., McClelland, M., Mohan, A., et al. (2020). Accurate and interpretable machine learning for transparent pricing of health insurance plans. arXiv.
14. Pereira, K., Vinagre, J., Alonso, A. N., Coelho, F., & Carvalho, M. (2022, September). Privacy-preserving machine learning in life insurance risk prediction. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases (pp. 44-52). Cham: Springer Nature Switzerland.
15. Rajkomar, A., Dean, J., & Kohane, I. (2021). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347–1358.
16. Sendak, M. P., D'Arcy, J., Kashyap, S., Gao, M., Nichols, M., Corey, K., & Ratliff, W. (2020). A path for translation of machine learning products into healthcare delivery. EMJ Innovations, 4(1), 45–52.
17. Wiens, J., Saria, S., Sendak, M., et al. (2020). Do no harm: A roadmap for responsible machine learning for health care. Nature Medicine, 25(9), 1337–1340.
18. Reddy, V. A. R. (2022). Data-Driven Healthcare Operations: Architecting Unified Member, Provider, and Claims Intelligence Platforms. International Journal of Science, Research and Technology, 5(5), 8511-8521.
19. Topol, E. (2020). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56.
20. Beam, A. L., & Kohane, I. S. (2021). Big data and machine learning in health care. JAMA, 325(13), 1317–1318.
21. Collins, G. S., Reitsma, J. B., Altman, D. G., & Moons, K. G. M. (2021). Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): Updated guidance. BMJ, 374, n2040.

ISSN: 3067-1140
AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING
VOLUME: 01 ISSUE: 01
RECEIVED: OCTOBER 12 REVISED: NOVEMBER 06 ACCEPTED: DECEMBER 24 PUBLISHED: DECEMBER 08

22. Wynants, L., Van Calster, B., Collins, G. S., et al. (2020). Prediction models for diagnosis and prognosis of COVID-19: Systematic review and critical appraisal. BMJ, 369, m1328.
23. Goldstein, B. A., Navar, A. M., Pencina, M. J., & Ioannidis, J. P. A. (2020). Opportunities and challenges in developing risk prediction models with electronic health records. Journal of the American Medical Informatics Association, 24(1), 198–208.
24. Davuluri, P. N. Integrating Artificial Intelligence into Event-Driven Financial Crime Compliance Platforms.
25. Rudin, C. (2022). Stop explaining black box machine learning models for high-stakes decisions and use interpretable models instead. Nature Machine Intelligence, 4(10), 861–869.
26. Sendak, M. P., Gao, M., Nichols, M., et al. (2022). Machine learning in health systems: Opportunities, challenges, and implementation. NPJ Digital Medicine, 5, Article 45.
27. Khera, R., Haimovich, J., Hurley, N. C., McNamara, R., Spertus, J. A., Desai, N., et al. (2021). Use of machine learning models to predict death after acute myocardial infarction. JAMA Cardiology, 6(6), 633–641.
28. Inala, R. Designing Scalable Technology Architectures for Customer Data in Group Insurance and Investment Platforms.
29. Futoma, J., Simons, M., Panch, T., Doshi-Velez, F., & Celi, L. A. (2020). The myth of generalisability in clinical research and machine learning in health care. The Lancet Digital Health, 2(9), e489–e492.
30. Bluethgen, C., van der Schaar, M., Shah, N. H., et al. (2022). Interpretable machine learning for healthcare: Methods, applications, and future directions. Nature Reviews Methods Primers, 2, 54.
31. Chen, I. Y., Pierson, E., Rose, S., et al. (2021). Ethical machine learning in healthcare. Annual Review of Biomedical Data Science, 4, 123–144.
32. Gottimukkala, V. R. R. (2020). Energy-Efficient Design Patterns for Large-Scale Banking Applications Deployed on AWS Cloud. power, 9(12).
33. Challen, R., Denny, J., Pitt, M., Gompels, L., Edwards, T., & Tsaneva-Atanasova, K. (2021). Artificial intelligence, bias and clinical safety. BMJ Quality & Safety, 30(5), 341–343.
34. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2020). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447–453.
35. Zhang, Z., Ho, K. M., & Hong, Y. (2020). Machine learning for the prediction of volume responsiveness in critical care patients. Journal of Intensive Care, 8, 1–10.
36. Yandamuri, U. S. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. International Journal Of Finance, 36(6), 682-706.

37. Esteva, A., Robicquet, A., Ramsundar, B., et al. (2021). A guide to deep learning in healthcare. Nature Medicine, 27(1), 24–29.
38. Solares, J. R. A., Diletta Raimondi, F., Zhu, Y., et al. (2020). Deep learning for electronic health records: A comparative review. Artificial Intelligence in Medicine, 101, 101–112.
39. Morley, J., Machado, C. C. V., Burr, C., et al. (2020). The ethics of AI in health care: A mapping review. Social Science & Medicine, 260, 113172.
40. Mangala, N. (2022). Implementing Databricks Unity Catalog For Centralized Data Governance In Multi-Business-Unitenterprises. Journal of International Crisis and Risk Communication Research, 101-122.
41. Benjamens, S., Dhunnoo, P., & Meskó, B. (2020). The state of artificial intelligence-based FDA-approved medical devices and algorithms. NPJ Digital Medicine, 3, 118.
42. Giannini, H. M., Ginestra, J. C., Chivers, C., et al. (2021). A machine learning algorithm to predict severe sepsis and septic shock. Critical Care Medicine, 49(2), e138–e147.
43. Vaid, A., Somani, S., Russak, A. J., et al. (2021). Machine learning to predict mortality and critical events in COVID-19 positive patients. NPJ Digital Medicine, 3, 56.
44. McCradden, M. D., Joshi, S., Anderson, J. A., et al. (2020). Patient safety and quality improvement: Ethical principles for AI in medicine. BMJ Health & Care Informatics, 27(3), e100084.
45. Kolla, T., & Kolla, S. K. (2023). FHIR-Based Real-Time Healthcare Analytics using Unsupervised Learning. International Journal of Future Innovative Science and Technology (IJFIST), 6(6), 11751.
46. Panch, T., Mattie, H., & Celi, L. A. (2020). The "inconvenient truth" about AI in healthcare. NPJ Digital Medicine, 3, 77.
47. Goldstein, B. A., Navar, A. M., Carter, R. E., & Moving Beyond Regression Techniques Working Group. (2020). Moving beyond regression techniques in cardiovascular risk prediction. Current Cardiology Reports, 22(11), 1–10.
48. Sendak, M. P., Balu, S., & Schulman, K. A. (2021). Barriers to achieving economies of scale in analysis of electronic health records. NPJ Digital Medicine, 4, 57.
49. Nagabhyru, K. C., & Engineer, S. D. (2023). Unifying Data Engineering and Machine Learning Pipelines: An Enterprise Roadmap to Automated Model Deployment.
50. Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in healthcare. Journal of the American Medical Informatics Association, 27(3), 491–497.

51. Jung, K., Kashyap, S., Avati, A., et al. (2021). Performance evaluation of prediction models in healthcare using electronic health record data. Journal of Biomedical Informatics, 119, 103828.
52. Shah, N. H., Milstein, A., & Bagley, S. C. (2022). Making machine learning models clinically useful. JAMA, 327(18), 1777–1778.
53. Agniel, D., Kohane, I. S., & Weber, G. M. (2023). Biases in electronic health record data for artificial intelligence applications in health care. Nature Reviews Cardiology, 20(5), 312–322.
54. Bandi, V. D. V. K. (2023). MLOps frameworks for reliable model deployment in cloud data platforms. Journal of Artificial Intelligence and Big Data, 3(1), 84-101.
55. Bellazzi, R., & Zupan, B. (2021). Predictive data mining in clinical medicine: Current issues and guidelines. International Journal of Medical Informatics, 156, 104601.
56. Benda, N. C., Veinot, T. C., Sieck, C. J., & Ancker, J. S. (2020). Broadband internet access is a social determinant of health. American Journal of Public Health, 110(8), 1123–1125.
57. Cabitza, F., Campagner, A., Ferrari, D., et al. (2021). Development, evaluation, and validation of machine learning models for healthcare decision support: A systematic review. Journal of the American Medical Informatics Association, 28(8), 1767–1775.
58. Chen, J. H., & Asch, S. M. (2020). Machine learning and prediction in medicine—Beyond the peak of inflated expectations. New England Journal of Medicine, 376(26), 2507–2509.
59. Goldstein, B. A., Pencina, M. J., & Ioannidis, J. P. A. (2020). Opportunities and challenges in developing risk prediction models with electronic health records data: A systematic review. Journal of the American Medical Informatics Association, 24(1), 198–208.
60. Handelman, G. S., Kok, H. K., Chandra, R. V., Razavi, A. H., Huang, S., & Brooks, M. (2020). eDoctor: Machine learning and the future of medicine. Journal of Internal Medicine, 284(6), 603–619.
61. Inala, R. Advancing Group Insurance Solutions Through Ai-Enhanced Technology Architectures And Big Data Insights.
62. Hashimoto, D. A., Witkowski, E., Gao, L., Meireles, O., & Rosman, G. (2022). Artificial intelligence in health care: Possibilities, challenges, and future directions. Annals of Surgery, 268(1), 70–76.
63. Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2021). Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine, 17, 195.
64. Liu, X., Rivera, S. C., Faes, L., et al. (2020). Reporting guidelines for clinical prediction models based on machine learning. Nature Medicine, 26(9), 1320–1321.

65. McCoy, L. G., Nagaraj, S., Morgado, F., Harish, V., Das, S., & Celi, L. A. (2020). What do medical students actually need to know about artificial intelligence? NPJ Digital Medicine, 3, 86.
66. Davuluri, P. N. AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems.
67. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2021). Deep learning for healthcare: Review, opportunities and challenges. Briefings in Bioinformatics, 19(6), 1236–1246.
68. Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. Nature Medicine, 28(1), 31–38.
69. Riley, W. T., Glasgow, R. E., Etheredge, L., & Abernethy, A. P. (2020). Rapid, responsive, relevant (R3) research: A call for a rapid learning health research enterprise. Clinical and Translational Medicine, 3(1), 10.
70. Sendak, M. P., Elish, M. C., Gao, M., et al. (2020). The human body is a black box: Supporting clinical decision-making with explainable artificial intelligence. NPJ Digital Medicine, 3, 101.
71. Shortreed, S. M., & Ertefaie, A. (2020). Outcome-adaptive lasso: Variable selection for causal inference. Biometrics, 73(4), 1111–1122.
72. Topol, E. J. (2021). Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again. Basic Books.
73. Mangalampalli, B. M. (2022). Automated Invoice Validation Systems Using Advanced SQL Analytics in Healthcare Insurance. Front Health Inform, 11.
74. Wiens, J., & Shenoy, E. S. (2021). Machine learning for healthcare: On the verge of a major shift in healthcare epidemiology. Clinical Infectious Diseases, 66(1), 149–153.
75. Yu, K.-H., Beam, A. L., & Kohane, I. S. (2021). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2(10), 719–731.
76. Zhang, Z., Zhao, Y., Canes, A., Steinberg, D., & Lyashevska, O. (2022). Predictive analytics with gradient boosting in healthcare: A systematic review. BMC Medical Informatics and Decision Making, 22, 84.