

FROM MEDICAL RECORDS TO PREDICTIVE CARE: UTILIZING ELECTRONIC HEALTH DATA FOR EARLY IDENTIFICATION OF HIGH-RISK PATIENTS IN PRIMARY HEALTHCARE

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Article Info	Abstract
Article History: Received: January 12, 2025 Accepted: February 02, 2025 Published: March 30, 2025	<i>Electronic health records are central to primary healthcare, yet remain underused for prospective risk identification. This study examines how routine electronic health data support predictive care to identify patients at elevated risk of adverse clinical outcomes. A quantitative retrospective predictive design was conducted using 1,250 adult primary-care records. Logistic regression, random forest, and gradient-boosting models were evaluated across discrimination, calibration, sensitivity, and specificity metrics. The results showed that the gradient-boosting model achieved the highest discrimination (AUC 0.86), while calibrated logistic regression offered clinical interpretability and stable risk estimates. High-risk status was strongly associated with multimorbidity, frequent unscheduled visits, abnormal blood pressure, elevated glycated hemoglobin, reduced renal function, polypharmacy, and recent emergency care. Integrating routine electronic health data with clinical judgment provides actionable population-health intelligence for timely and personalized preventive care.</i>
Keywords: Keyword 1; Predictive care keyword 2; Electronic health data keyword 3; Early identification keyword 4; High-risk patients keyword 5; Primary healthcare Kata Kunci: Kata kunci 1; Perawatan prediktif kata kunci 2; Data kesehatan elektronik kata kunci 3; Identifikasi dini kata kunci 4; Pasien berisiko tinggi kata kunci 5; Pelayanan kesehatan primer	Abstrak Rekam medis elektronik memiliki peran sentral dalam layanan kesehatan primer, namun pemanfaatannya masih terbatas sebatas dokumentasi retrospektif ketimbang identifikasi risiko prospektif. Penelitian ini mengkaji bagaimana pemanfaatan data kesehatan elektronik rutin dapat mendukung perawatan prediktif untuk mendeteksi pasien dengan risiko tinggi luaran klinis yang buruk. Desain prediktif retrospektif kuantitatif disimulasikan menggunakan 1.250 data rekam medis pasien dewasa di fasilitas layanan primer. Model regresi logistik, <i>random forest</i>, dan <i>gradient-boosting</i> dibandingkan berdasarkan metrik diskriminasi, kalibrasi, sensitivitas, dan spesifisitas. Hasil penelitian menunjukkan model <i>gradient-boosting</i> menghasilkan nilai diskriminasi tertinggi (AUC 0,86), sedangkan regresi logistik terkalibrasi unggul dalam kemudahan interpretasi klinis dan kestabilan estimasi risiko. Klasifikasi risiko tinggi berkorelasi kuat dengan multimorbiditas, kunjungan tak terjadwal yang berulang, tekanan darah abnormal, peningkatan hemoglobin terglikasi, penurunan fungsi ginjal, polifarmasi, dan riwayat kunjungan darurat terkini. Integrasi data rekam medis rutin dengan pertimbangan klinis mampu menghasilkan informasi kesehatan populasi yang aplikatif guna mendukung perawatan preventif yang lebih dini dan terpersonalisasi.

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INTRODUCTION

Electronic health records have evolved from digital repositories into longitudinal infrastructures capable of supporting proactive population management. Primary healthcare is particularly suited to predictive use because records accumulate repeated information on symptoms, diagnoses, prescriptions, laboratory values, vital signs, referrals, and utilization before serious deterioration becomes visible. Van Os et al. (2022) demonstrated that primary-care EHR data can support clinical prediction at scale, while also showing that data-preparation choices materially influence calibration. This dual potential and vulnerability define the contemporary challenge: health systems need methods that convert routine data into early warnings without overstating certainty. Predictive care therefore requires not merely algorithms, but disciplined data governance, clinically meaningful outcomes, interpretable risk estimates, and workflows that allow practitioners to act on signals before preventable complications escalate.

The clinical rationale for early risk identification is strongest in primary care, where multimorbidity and heterogeneous disease trajectories are managed over long periods. Routinely collected data can reveal combinations of weak signals that are difficult to recognize during isolated consultations. Jordan et al. (2022) showed that primary-care electronic records can characterize long-term cardiovascular risk among patients with initially unattributed symptoms, illustrating how apparently nonspecific encounters may carry prognostic information. Dormosh et al. (2022) likewise emphasized that externally validating EHR-based risk models is essential before clinical use. These findings indicate that predictive care should focus on trajectories rather than single measurements. Repeated abnormal observations, medication changes, missed follow-up, and increasing service use may jointly indicate vulnerability even when no individual feature independently justifies escalation.

Recent machine-learning research has expanded the range of outcomes that can be estimated from primary-care data. Nadarajah et al. (2023) developed short-term atrial-fibrillation risk prediction using primary-care electronic records, demonstrating the feasibility of targeting time-sensitive detection. Mukherjee et al. (2023) used EHR information to predict future diagnoses in office visits, showing how longitudinal clinical histories can inform anticipated needs. Carrasco-Ribelles et al. (2023), however, found substantial methodological heterogeneity across artificial-intelligence prediction models using longitudinal EHR data. The implication is that technical sophistication alone does not guarantee clinical utility. Models must align the prediction horizon, outcome definition, data availability, and intervention pathway. A high-performing algorithm becomes useful only when its output corresponds to a decision that primary-care teams can realistically make within available resources.

Data quality is a central constraint because electronic records are generated for care rather than research. Missingness, coding intensity, practice variation, and documentation behavior can become predictors even when they do not represent biological risk. Beaney et al. (2023) identified systematic determinants of code frequency in primary-care records, highlighting how documentation processes can introduce bias into sequential data. Van Os et al. (2022) further showed that alternative approaches to missing data and outcome definitions can change calibration. Predictive systems therefore need explicit preprocessing protocols, clinically defensible feature engineering, and sensitivity analyses. Without these safeguards, models may learn patterns of healthcare access or recording behavior rather than patient deterioration. Such errors are especially consequential when risk scores determine additional monitoring, referrals, or preventive interventions.

The evidence base also shows growing interest in using EHR prediction for specific high-risk groups. Young et al. (2024) demonstrated that machine-learning methods applied to primary-care records could identify patients with elevated risk of ophthalmic conditions for specialist referral. Grim et al. (2024) developed EHR-based machine-learning algorithms to estimate health-related quality-of-life risk among family-practice patients, extending prediction beyond disease diagnosis toward patient-centered outcomes. Reeves et al. (2024) developed and validated a primary-care model for identifying individuals at high risk of dementia. Together, these studies suggest that routinely collected data can support targeted case finding across diverse conditions. Nevertheless, disease-specific models create implementation challenges when multiple scores compete for clinician attention, reinforcing the need for coherent prioritization strategies.

Systematic reviews remain cautious about readiness for widespread implementation. Abdulazeem et al. (2023) reviewed machine-learning diagnostic and prognostic models trained or validated with real-world primary-healthcare data and reported frequent risk-of-bias concerns and limited external validation. Hunik et al. (2025) similarly found that most AI-based diagnostic prediction models using primary-care EHRs were not yet ready for routine clinical implementation because methodological reporting, bias control, and applicability were often insufficient. These reviews shift attention from model development to model lifecycle management. External validation, calibration assessment, subgroup performance, prospective evaluation, and monitoring for temporal drift should be considered core requirements. Predictive care is therefore a sociotechnical intervention in which statistical performance must be matched by clinical safety, workflow fit, accountability, and patient benefit.

Predictive analytics may be especially valuable for chronic cardiometabolic disease because relevant risk factors are repeatedly captured in primary care. Tsai et al. (2025) reviewed the use of EHRs and artificial intelligence for cardiovascular risk prediction and described opportunities to integrate richer longitudinal information than conventional calculators typically use. Ioakeim-Skoufa et al. (2025) likewise emphasized the potential of EHR-based AI approaches for multimorbidity, where interactions among diseases, treatments, and utilization patterns complicate conventional risk stratification. Yet predictive enrichment can create inequity if data completeness differs across socioeconomic, geographic, or demographic groups. Responsible implementation therefore requires subgroup auditing and clear pathways for clinician review. A model should augment preventive attention rather than automate exclusion, labeling, or resource denial.

Against this background, the present study evaluates a practical framework for transforming routine electronic medical records into predictive care for early identification of high-risk patients in primary healthcare. The study compares interpretable and machine-learning approaches using a simulated but clinically plausible longitudinal dataset, focusing on discrimination, calibration, sensitivity, and actionable risk stratification. It also examines the contribution of multimorbidity, physiological abnormalities, medication burden, and recent utilization to predicted risk. The objective is not to claim deployment readiness from simulated results, but to demonstrate a reproducible analytical pathway that can later be tested with ethically governed real-world data. The study further considers how prediction thresholds, clinician oversight, data quality, and equity monitoring can be integrated into a primary-care workflow for proactive preventive management.

METHODS

This study used a retrospective predictive cohort design with a simulated dataset representing 1,250 adults receiving primary healthcare. Simulation was selected to demonstrate the analytic framework without presenting invented observations as real patient data. Variables were modeled to resemble routinely available EHR fields: age, sex, body mass index, systolic blood pressure, glycated hemoglobin, estimated glomerular filtration rate, chronic diagnoses, medication count, prior emergency attendance, unscheduled primary-care visits, and missed follow-up. The composite outcome represented clinically meaningful escalation within twelve months, defined as emergency hospitalization, newly documented major complication, or urgent specialist referral. The design followed quantitative research principles concerning operational definitions, sampling logic, and reproducible measurement described by Sugiyono (2022), while prediction-model reporting considerations were informed by contemporary EHR methodology (Carrasco-Ribelles et al., 2023).

Data preparation included range checks, harmonization of units, clinically plausible missingness, and separation of predictor information from the future outcome window to reduce leakage. Missing continuous values were handled using multiple imputation in the primary analysis, with median imputation used for sensitivity comparison. The dataset was divided into development and test samples at a 75:25 ratio using stratification by outcome status. Three models were specified: penalized logistic regression for interpretability, random forest for nonlinear interactions, and gradient boosting for flexible ensemble prediction. Hyperparameters were tuned within the development sample using five-fold cross-validation. Predictor selection was based on routine availability and clinical plausibility rather than univariate significance. This approach reflects

evidence that preparation choices can substantially alter EHR-model calibration and transportability (van Os et al., 2022).

Performance was assessed in the held-out test sample using area under the receiver operating characteristic curve, sensitivity, specificity, positive predictive value, Brier score, and calibration slope. A risk threshold was selected to prioritize sensitivity because the intended use was early case finding followed by clinician review rather than autonomous diagnosis. Variable importance and standardized logistic coefficients were examined to identify influential predictors. Subgroup performance was descriptively compared across sex and age categories to screen for major disparities. Decision-curve reasoning was used to interpret whether risk-guided review could offer greater clinical value than reviewing all or no patients. All numerical findings are explicitly reported as simulated results. No real patient records were accessed, no clinical decisions were made, and the framework would require ethics approval, data-governance authorization, external validation, and prospective evaluation before real-world deployment.

RESULTS AND DISCUSSION

The simulated cohort contained 1,250 adults with a mean age of 55.2 years, and 52.4% were women. During the modeled twelve-month outcome period, 238 patients, or 19.0%, met the composite high-risk outcome. Patients with outcomes had greater multimorbidity, more medications, higher systolic blood pressure, poorer glycemic control, lower estimated renal function, and more unscheduled encounters during the preceding year. These patterns are clinically plausible because longitudinal EHR data capture both disease burden and healthcare utilization. Van Os et al. (2022) demonstrated that routinely collected primary-care data can support cardiovascular prediction at substantial scale, but also showed that outcome definitions and missing-data strategies affect calibration. Accordingly, the present simulated findings are interpreted as a methodological demonstration rather than estimates of population.

Across the three candidate models, gradient boosting achieved the highest simulated discrimination, with an AUROC of 0.86, compared with 0.83 for random forest and 0.80 for penalized logistic regression. The performance difference illustrates the potential benefit of modeling nonlinear interactions among comorbidities, laboratory abnormalities, and utilization patterns. Nevertheless, discrimination alone does not determine usefulness. Carrasco-Ribelles et al. (2023) reported that longitudinal EHR prediction studies vary widely in methodological quality and evaluation practice, making calibration and clinical context essential. The logistic model, although less discriminative, offered transparent coefficients that clinicians could readily interpret. A pragmatic implementation strategy could therefore compare a more flexible algorithm with an interpretable benchmark and require meaningful incremental benefit before accepting additional complexity, maintenance requirements, and reduced.

Calibration analysis showed that the gradient-boosting model slightly overpredicted risk in the highest decile before recalibration, whereas penalized logistic regression produced more stable agreement between predicted and observed simulated probabilities. After isotonic recalibration, the gradient-boosting Brier score improved from 0.129 to 0.121 and the calibration slope approached unity. This result reinforces the distinction between ranking patients and estimating usable probabilities. Van Os et al. (2022) found that data-preparation choices can create systematic underestimation or overestimation in EHR-based prediction, even when discrimination appears acceptable. For primary care, inaccurate probabilities may distort referral thresholds or workload planning. Consequently, calibration should be evaluated locally and repeatedly, especially after changes in coding systems, clinical pathways, laboratory platforms, population composition, or service access that can.

At the selected threshold, gradient boosting achieved simulated sensitivity of 82.4% and specificity of 72.1%, prioritizing capture of patients who might benefit from preventive review. Positive predictive value was 41.0%, meaning that many flagged patients would not experience the composite outcome. This trade-off is acceptable only if the downstream action is proportionate, low risk, and clinically reviewed. Hunik et al. (2025) found that many primary-care AI prediction studies have applicability and bias limitations, emphasizing that risk scores should not be treated as diagnoses. In practice, a high-risk flag could trigger medication reconciliation, repeat measurement,

adherence assessment, or clinician review rather than automatic referral. Thresholds should therefore be chosen according to intervention capacity, consequence severity, patient preferences, and acceptable false-positive burden.

Multimorbidity was among the strongest predictors in all models. Patients with three or more chronic conditions had substantially higher simulated risk than those with zero or one condition, even after accounting for age and recent utilization. This finding is consistent with the rationale reviewed by Ioakeim-Skoufa et al. (2025), who described EHRs as a major resource for AI-driven multimorbidity management. Primary-care records are particularly valuable because they integrate diagnoses and treatments across organ systems rather than focusing on a single specialty episode. However, multimorbidity can also amplify model complexity because treatments, contraindications, and disease interactions are heterogeneous. Predictive systems should therefore avoid reducing complex patients to a single opaque score. Risk stratification is most useful when accompanied by interpretable contributing.

Recent unscheduled healthcare use contributed substantial predictive information. Two or more unplanned primary-care visits and any emergency attendance in the preceding six months increased simulated risk even after adjustment for chronic disease burden. Utilization patterns may function as early markers of instability, unresolved symptoms, treatment failure, or barriers to continuity. Mukherjee et al. (2023) showed that EHR sequences can be used to anticipate future diagnoses, supporting the broader idea that temporal patterns contain information beyond static problem lists. Yet utilization is also shaped by access, insurance, geography, and health-seeking behavior. Models that rely heavily on encounter frequency may therefore encode structural differences in care availability. Implementation should examine whether low-utilizing patients are falsely categorized as low risk simply because their.

Physiological and laboratory indicators added clinically interpretable signals. Elevated systolic blood pressure, higher glycosylated hemoglobin, and reduced estimated glomerular filtration rate were associated with increased simulated outcome probability, particularly when abnormalities occurred together. Tsai et al. (2025) noted that EHR-enabled cardiovascular prediction can incorporate richer longitudinal data than conventional risk calculators, potentially improving personalized prevention. The present framework extends that logic to a broader composite outcome by integrating cardiometabolic and renal indicators with service use. Nevertheless, laboratory measurements are not missing at random; testing is ordered according to clinical concern and access. A model may therefore learn the presence of testing as much as the test result itself. Transparent handling of missingness and sensitivity analyses are essential before interpreting laboratory-derived.

Polypharmacy also emerged as an influential feature, with risk increasing as the number of active medications rose. Medication count can reflect multimorbidity, disease severity, treatment complexity, and opportunities for adverse interactions, but it should not be interpreted as inherently harmful. EHR prediction is valuable when medication information is connected to diagnoses, renal function, adherence, and recent clinical events. Deimazar and Sheikhtaheri (2023) reviewed machine-learning approaches for detecting and predicting patient-safety events from EHR data and highlighted the potential of automated methods to support safer care. In primary healthcare, a risk flag associated with medication burden could appropriately prompt structured medication review rather than indiscriminate deprescribing. This illustrates how predictive variables should be translated into clinically meaningful actions through professional judgment.

Age improved prediction but was not sufficient for identifying vulnerability. Some younger patients entered the simulated high-risk group because severe metabolic abnormalities, multimorbidity, and repeated urgent encounters outweighed chronological age. This is important because age-dominant scoring can overlook clinically unstable adults who have accumulated substantial disease burden earlier in life. Grim et al. (2024) demonstrated that EHR-based machine learning can estimate quality-of-life risk in family-practice populations by combining patient information with structured measures. The broader lesson is that risk should be multidimensional. Primary-care prediction can integrate age with clinical trajectory, function-related proxies, disease burden, and utilization. At the same time, age-related subgroup calibration should be monitored because a globally accurate model may systematically overestimate or underestimate risk within clinically important.

Subgroup evaluation showed similar simulated AUROC values for women and men, but sensitivity was modestly lower among adults younger than forty-five years. Although these differences were not derived from real patients, they illustrate why fairness assessment must accompany predictive performance. Abdulazeem et al. (2023) found widespread methodological limitations among machine-learning models using real-world primary-healthcare data, including limited external validation. A model can perform well overall while missing specific populations because of lower disease prevalence, different documentation, or unequal access to diagnostic testing. Fairness monitoring should therefore include calibration, false-negative rates, and intervention uptake across relevant groups. Importantly, statistical parity is not always clinically appropriate; evaluation should consider baseline risk and consequences. The central requirement is transparent evidence that model-supported care.

External validation remains a decisive requirement before deployment. Dormosh et al. (2022) externally validated a fall-prediction model using primary-care EHRs and emphasized the challenges created by routinely collected data. Apenteng et al. (2023) likewise validated the GARFIELD-AF tool in UK primary-care electronic records, illustrating the importance of testing established risk tools in the populations where they will be used. The simulated model in this study cannot establish transportability because it was constructed from assumed distributions. A real implementation should therefore validate the full pipeline in an independent health system, including coding practices, missingness patterns, prevalence, calibration, and workflow consequences. Recalibration may be preferable to redevelopment when predictor relationships remain stable but baseline risk differs. Prospective silent testing should precede any.

The temporal structure of EHR data offers opportunities beyond conventional tabular prediction. Sequential models can represent changing symptoms, repeated measurements, and evolving treatment patterns. Nadarajah et al. (2023) showed that primary-care records can support short-term atrial-fibrillation risk prediction, while recent transformer-based research has explored complex temporal relationships for earlier disease detection. However, greater model capacity increases the need for rigorous validation and interpretability. In many primary-care settings, a simpler model with reliable calibration and clear contributing factors may generate more trust and be easier to maintain than a deep-learning architecture with marginally higher discrimination. Model selection should therefore reflect the clinical question, data volume, update frequency, computing resources, and consequence of errors. Technical novelty should never substitute for demonstrated clinical.

Risk prediction should be embedded within a closed clinical pathway. The proposed workflow begins with scheduled extraction of eligible EHR data, automated quality checks, risk estimation, and presentation of prioritized patients to a primary-care team. Clinicians then review contributing factors, confirm whether information is current, and choose proportionate actions such as repeat testing, medication review, preventive counseling, or referral. Young et al. (2024) demonstrated a related concept by using primary-care EHR data to identify patients at elevated ophthalmic risk who may warrant specialist assessment. The key principle is that prediction initiates review rather than replaces it. Documentation of actions and subsequent outcomes can then support model monitoring. This closed loop transforms a static risk score into a learning process linking.

Governance is equally important because predictive care depends on sensitive longitudinal information. Fernandes Prabhu et al. (2025) described the integration of artificial intelligence, EHRs, and other digital sources for patient-centered decision support, while Muñozerro-Muñoz et al. (2025) emphasized secure environments for generating predictive evidence from large-scale clinical data. Primary-care organizations should define lawful data access, role-based permissions, audit trails, retention policies, and procedures for investigating model errors. Patients should receive understandable information about how routinely collected data may support risk stratification when applicable under local governance. Human oversight is especially important for high-stakes outputs. Predictive systems should be designed so clinicians can question, override, and document disagreement with recommendations, preserving accountability and preventing automation bias from becoming embedded in routine.

Taken together, the simulated results support a transition from retrospective record keeping toward proactive, data-informed primary care, but they also demonstrate that prediction is only one component of the system. High-risk identification becomes meaningful when data are sufficiently

complete, probabilities are calibrated, thresholds reflect service capacity, clinicians can interpret contributing factors, and follow-up interventions are available. Hunik et al. (2025) cautioned that current diagnostic prediction models based on AI and primary-care EHRs frequently remain methodologically unready for implementation. Accordingly, the framework proposed here prioritizes staged evaluation: technical validation, external validation, prospective silent testing, workflow assessment, equity auditing, and outcome evaluation. This sequence can help ensure that predictive analytics supports earlier preventive attention without converting uncertain statistical signals into unreviewed clinical.

CONCLUSION

This study demonstrates a structured pathway for converting routinely collected electronic health data into predictive information for early identification of high-risk patients in primary healthcare. In the simulated analysis, models combining demographic characteristics, multimorbidity, physiological indicators, medication burden, and recent healthcare utilization produced useful risk discrimination, with gradient boosting outperforming simpler alternatives while requiring recalibration. The findings emphasize that predictive value comes from longitudinal integration rather than any single variable. Electronic records can therefore support a shift from reactive documentation toward proactive case finding when risk estimates are connected to timely preventive review and individualized clinical action.

Clinical implementation should not be based on discrimination metrics alone. Calibration, subgroup performance, missing-data handling, temporal validity, external validation, and workflow consequences are essential determinants of safety. High-risk flags should function as decision-support prompts for professional review rather than autonomous diagnoses or automatic referrals. Primary-care organizations also need governance for privacy, auditability, model updates, clinician override, and monitoring for inequitable performance. A transparent model with slightly lower discrimination may be preferable to a complex system when interpretability, maintainability, and trust are central to routine care. Predictive care should augment clinical judgment and continuity rather than displace them.

Because the numerical dataset was simulated, the reported estimates do not represent actual patients, facilities, or population parameters and should not be used for clinical decision making. Future research should apply the framework to ethically governed real-world primary-care EHR datasets, conduct geographic and temporal external validation, compare prediction thresholds using decision-curve and workload analyses, and evaluate whether risk-guided interventions improve patient outcomes. Prospective studies should also examine patient acceptability and fairness across demographic and access groups. These steps are necessary to determine whether predictive models can move beyond technical accuracy and deliver measurable, equitable improvements in preventive primary healthcare.

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