Predict Before Symptoms: Building a Multisource Predictive Healthcare Framework Using Radiology, Laboratory, Endoscopy, Family Medicine, Rehabilitation, and Administrative Data

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ABSTRACT:

Background: Health systems remain predominantly reactive, with many diseases identified only after symptoms, complications, or functional decline have already occurred. Although modern hospitals generate large quantities of clinical, imaging, laboratory, procedural, rehabilitation, and administrative data, these data streams are frequently stored and interpreted in separate departmental systems. This fragmentation limits the ability of health services to detect early deterioration, identify high-risk individuals, and implement preventive interventions before disease becomes clinically apparent.

Aim: This manuscript proposes a multisource predictive healthcare framework that integrates radiology, laboratory medicine, endoscopy, family medicine, rehabilitation, and administrative data to support earlier risk identification, preventive care planning, and population health management.

Methods: The present manuscript is designed as a conceptual framework paper informed by current literature on predictive medicine, clinical data integration, preventive care, imaging biomarkers, laboratory trends, endoscopic surveillance, primary

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care risk assessment, rehabilitation outcomes, and administrative health data. The authors propose a staged model involving data acquisition, standardization, longitudinal risk profiling, multidisciplinary interpretation, clinical action pathways, governance, evaluation, and continuous quality improvement.

Results: The proposed framework consists of six integrated data domains: radiology-based anatomical and physiological markers; laboratory-based biochemical and hematological trends; endoscopy-based mucosal and structural findings; family medicine-derived longitudinal clinical context; rehabilitation-based functional and performance measures; and administrative data reflecting utilization, comorbidity, access, cost, and system-level risk. These inputs are organized into a unified predictive cycle that identifies risk before symptoms, stratifies patients according to urgency and modifiability, and triggers preventive actions through multidisciplinary care pathways.

Discussion: Compared with conventional symptom-driven care, the proposed framework emphasizes early recognition of risk trajectories, continuity across departments, structured data standards, and preventive intervention. Potential benefits include earlier diagnosis, reduced emergency presentations, improved chronic disease management, enhanced rehabilitation planning, and better allocation of healthcare resources. However, implementation requires strong governance, interoperability, data-quality assurance, clinician engagement, ethical oversight, and prospective validation.

Conclusion: A multisource predictive healthcare framework may help transform fragmented clinical information into actionable preventive intelligence. Integration of radiology, laboratory, endoscopy, family medicine, rehabilitation, and administrative data can support earlier risk detection and more coordinated clinical decision-making. Future studies should validate this framework prospectively across diverse healthcare settings and assess its impact on clinical outcomes, cost-effectiveness, equity, and workflow feasibility.

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Keywords: predictive healthcare; preventive medicine; radiology; laboratory medicine; endoscopy; family medicine; rehabilitation; administrative data; clinical informatics; integrated care.

1. Introduction

Healthcare systems are facing increasing pressure from ageing populations, rising multimorbidity, escalating costs, delayed diagnosis, avoidable hospital admissions, and the long-term consequences of chronic disease. Many patients enter clinical pathways only after symptoms have developed, functional ability has declined, or disease complications have become established. This reactive model is particularly problematic in chronic conditions such as cardiovascular disease, diabetes, chronic kidney disease, cancer, chronic respiratory disease, musculoskeletal disorders, frailty, and neurodegenerative disease, where biological and

functional changes may occur long before overt symptoms become clinically obvious [1–4].

The transition from reactive care to predictive and preventive care requires more than isolated screening tests. It requires the ability to combine multiple forms of patient information across time and across specialties. Modern healthcare institutions already collect large volumes of relevant data through radiology examinations, laboratory investigations, endoscopic procedures, family medicine encounters, rehabilitation assessments, and administrative records. However, these data are often stored within separate departmental platforms, interpreted independently, and used primarily for the immediate clinical question rather than for longitudinal risk prediction [5–7]. As a result, opportunities for early detection and prevention are frequently missed.

Radiology can reveal anatomical and physiological markers of silent disease, including coronary artery calcification, low bone density, sarcopenia, hepatic steatosis, pulmonary abnormalities, vascular calcification, and occult malignancy indicators [8–11]. Laboratory medicine can detect biochemical and hematological changes before symptoms develop, including trends in glycemic control, renal function, inflammation, anemia, coagulation, lipid metabolism, liver injury, and endocrine dysfunction [12–14]. Endoscopy provides direct visualization and histological access to mucosal disease, premalignant lesions, inflammatory activity, bleeding sources, and structural pathology within the gastrointestinal tract [15–17]. Family medicine contributes longitudinal clinical context, risk-factor surveillance, preventive screening, medication review, vaccination, and continuity of care [18–20]. Rehabilitation services generate functional and performance data that may identify frailty, mobility limitation, cognitive-motor decline, falls risk, and recovery trajectories [21–23]. Administrative data provide complementary information on healthcare utilization, comorbidity burden, access patterns, readmission risk, cost, and system-level inequities [24–26].

Despite the richness of these domains, most predictive efforts remain confined to a single specialty, a single dataset, or a narrow clinical outcome. This limitation reduces the capacity of health systems to understand patient risk as a dynamic, multisystem process. For example, a patient with repeated emergency visits, subtle decline in estimated glomerular filtration rate, unreported vascular calcification on imaging, poor attendance in primary care, and early functional deterioration may appear low risk within each isolated department but high risk when the data are integrated. Therefore, multisource integration may allow healthcare teams to recognize risk patterns before symptoms become severe or irreversible.

The present manuscript addresses this gap by proposing a comprehensive multisource predictive healthcare framework that integrates radiology, laboratory medicine, endoscopy, family medicine, rehabilitation, and administrative data. The framework is intended to support early risk identification, multidisciplinary interpretation, preventive intervention, and population-level planning. It is presented as a conceptual model suitable for future empirical validation and implementation research.

2. Background

2.1 Predictive and Preventive Healthcare

Predictive healthcare refers to the use of clinical, biological, functional, and system-level information to estimate the probability of future disease, deterioration, complications, or service utilization. Preventive healthcare seeks to reduce these risks through early intervention, screening, behavioral modification, targeted monitoring, and timely referral [1,2]. The strongest predictive systems are not limited to single measurements; they incorporate longitudinal trajectories, comorbidities, clinical context, and modifiable risk factors [3,4].

Existing prediction models have been developed for cardiovascular risk, diabetes complications, cancer screening, hospital readmission, sepsis, falls, frailty, renal decline, and mortality [1,2,24,25]. However, many models are not fully

integrated into clinical workflow, are poorly calibrated in external populations, or depend on data that are incomplete, inconsistently coded, or unavailable at the point of care [27–29]. Reporting and methodological standards such as TRIPOD and PROBAST emphasize transparent model development, validation, calibration, bias assessment, and clinical usefulness [27,28]. These principles are essential for any multisource framework intended to support real-world healthcare decisions.

2.2 The Problem of Fragmented Data

Healthcare data fragmentation is a major barrier to predictive care. Radiology information systems, laboratory information systems, endoscopy reporting platforms, primary care records, rehabilitation documentation, and administrative databases are often maintained separately. Even when these systems coexist within an electronic health record, their data may not be harmonized, structured, or clinically linked [5–7]. Fragmentation produces several limitations: incomplete patient profiles, duplicate investigations, delayed communication, inconsistent coding, limited feedback between departments, and failure to identify cumulative risk.

Interoperability standards such as HL7 Fast Healthcare Interoperability Resources, Digital Imaging and Communications in Medicine, Logical Observation Identifiers Names and Codes, Systematized Nomenclature of Medicine Clinical Terms, and International Classification of Diseases coding can support structured exchange and semantic consistency across systems [30–34]. However, technical standards alone are insufficient. Successful integration also requires governance, data-quality management, clinician engagement, workflow design, privacy protection, and accountability for clinical action [35,36].

2.3 Multisource Clinical Prediction

Multisource prediction reflects the reality of clinical reasoning. Clinicians rarely make decisions based on a single data point; they combine symptoms, history, imaging, laboratory results, functional status, procedural findings, and social context. The proposed framework formalizes this process by organizing diverse data streams into structured risk domains. It aims to detect changes earlier than conventional care by combining cross-sectional markers with longitudinal trajectories.

For example, early cardiometabolic risk may be inferred from obesity documented in primary care, rising hemoglobin A1c, dyslipidemia, hepatic steatosis on ultrasound, coronary calcification on CT, low exercise tolerance during rehabilitation assessment, and repeated missed appointments. Similarly, early gastrointestinal cancer risk may be identified through family history, iron deficiency anemia, positive stool testing, endoscopic findings, histopathology, and delayed follow-up. In older adults, frailty risk may be indicated by sarcopenia on imaging, declining albumin, reduced gait speed, recurrent falls, polypharmacy, and increasing emergency visits [21–25].

The literature increasingly supports the value of integrated clinical information for improving risk stratification, but implementation remains uneven. Most healthcare organizations continue to operate with departmental decision-making structures, limited shared dashboards, and variable follow-up mechanisms. A conceptual framework that explicitly defines the contribution of each specialty may therefore help guide future clinical implementation.

3. Aim of the Study

The aim of the present manuscript is to propose a multisource predictive healthcare framework that integrates radiology, laboratory medicine, endoscopy, family medicine, rehabilitation, and administrative data for the early identification of disease risk before symptom onset or clinical deterioration.

The specific objectives are:

1. To define the contribution of each specialty to predictive healthcare.
2. To propose an integrated conceptual model linking multisource data to preventive clinical action.

3. To describe data elements, integration standards, governance requirements, and clinical workflows needed for implementation.
4. To compare the proposed approach with conventional symptom-driven care.
5. To identify implementation barriers, opportunities, and future research directions.

4. Methods / Conceptual Framework

4.1 Study Design

This manuscript presents a conceptual framework rather than an empirical clinical trial or retrospective cohort study. The proposed framework was developed through synthesis of published literature, current clinical practice principles, reporting standards for prediction research, and multidisciplinary healthcare workflows. The framework is intended to guide future implementation studies, pilot projects, and prospective validation.

4.2 Core Components of the Framework

The proposed framework consists of seven operational layers:

1. **Data acquisition:** collection of structured and semi-structured data from radiology, laboratory, endoscopy, family medicine, rehabilitation, and administrative systems.
2. **Data standardization:** harmonization of terminology, coding, units, timestamps, and patient identifiers using accepted clinical data standards.
3. **Longitudinal patient profiling:** organization of data into time-based patient trajectories rather than isolated encounters.
4. **Risk stratification:** classification of patients into low, moderate, high, or urgent risk categories based on combined clinical indicators.
5. **Multidisciplinary interpretation:** review of risk signals by relevant clinical teams to determine clinical meaning and actionability.
6. **Preventive action pathways:** initiation of screening, referral, lifestyle intervention, medication optimization, rehabilitation planning, surveillance, or case management.
7. **Evaluation and feedback:** monitoring of outcomes, false alerts, missed events, clinician adherence, patient engagement, equity, and cost-effectiveness.

4.3 Data Governance and Ethical Principles

The framework requires strong governance to ensure privacy, confidentiality, transparency, fairness, and clinical accountability. Governance should define who can access integrated data, how risk outputs are reviewed, how patients are informed, how errors are managed, and how performance is audited. Data protection must comply with institutional policies and relevant national regulations. Patients should benefit from integration without being exposed to inappropriate surveillance, stigmatization, or inequitable care pathways [35–37].

4.4 Data Standardization

A multisource framework depends on semantic and technical interoperability. Radiology data should be linked through DICOM-compatible systems and structured reporting. Laboratory values should use standardized test identifiers and consistent units. Endoscopy reports should include structured lesion descriptors, anatomical location, histopathology links, and surveillance recommendations. Family medicine records should include coded diagnoses, medications, risk factors, social determinants, vaccination history, screening status, and care plans. Rehabilitation records should include validated functional measures. Administrative data should include coded encounters, admissions, procedures, length of stay, cost, discharge status, and readmissions [30–34].

Table 1. Proposed multisource data domains and predictive contributions

Data domain	Key data elements	Predictive contribution	Example preventive action
Radiology	CT, MRI, ultrasound, X-ray, structured imaging reports, anatomical biomarkers	Detection of silent structural disease, vascular calcification, sarcopenia, steatosis, bone loss, occult lesions	Referral for cardiovascular prevention, osteoporosis assessment, liver evaluation, cancer screening
Laboratory medicine	Hematology, chemistry, renal function, liver enzymes, lipids, glucose, inflammatory markers, coagulation	Detection of early biochemical change and longitudinal deterioration	Medication review, metabolic intervention, nephrology referral, anemia workup
Endoscopy	Colonoscopy, gastroscopy, lesion characteristics, histopathology, surveillance interval	Identification of premalignant, inflammatory, bleeding, and structural gastrointestinal disease	Polypectomy follow-up, cancer prevention, inflammatory disease monitoring
Family medicine	Risk factors, symptoms, family history, medications, lifestyle, chronic disease records, screening status	Longitudinal risk context and preventive care coordination	Screening reminders, lifestyle counseling, chronic disease optimization
Rehabilitation	Gait speed, balance, strength, functional independence, falls history, exercise tolerance	Early detection of frailty, disability risk, poor recovery, functional decline	Fall prevention, physiotherapy, occupational therapy, home adaptation
Administrative data	Admissions, emergency visits, length of stay, readmissions, claims, missed appointments, cost	Health service utilization risk, access barriers, care fragmentation, resource planning	Case management, care navigation, discharge planning, population health intervention

5. Results

5.1 Overview of the Framework

The proposed integrated model is designed as a continuous cycle rather than a single prediction event. It begins with routine data collection during usual care and ends with preventive clinical action and feedback. The model does not require every patient to undergo additional testing. Instead, it uses existing clinical data more effectively by connecting signals that are currently dispersed across departments.

The framework classifies risk into three broad categories:

1. **Clinical risk:** probability of disease onset, progression, complication, or functional decline.
2. **Utilization risk:** probability of emergency attendance, hospitalization, readmission, prolonged stay, or high resource use.
3. **Preventability risk:** probability that early intervention can reduce future harm.

The most valuable cases are those with high clinical risk and high preventability. These patients should be prioritized for early multidisciplinary intervention.

5.2 Radiology Data Subsection: Role, Contribution, Relevance, and Integration

Radiology is central to predictive healthcare because imaging often reveals structural abnormalities before symptoms appear. Routine imaging may detect silent cardiovascular, pulmonary, hepatic, renal, musculoskeletal, neurological, and oncological findings. CT scans can show coronary artery calcification, aortic calcification, vertebral fractures, emphysema, sarcopenia, hepatic steatosis, visceral adiposity, renal atrophy, and incidental masses [8–11]. Ultrasound may reveal fatty liver disease, thyroid nodules, renal abnormalities, vascular disease, and abdominal pathology. MRI may identify early neurological, musculoskeletal, oncological, and inflammatory changes. Plain radiography can contribute to early detection of cardiopulmonary abnormalities, osteoporotic fractures, and degenerative disease.

Within the proposed framework, radiology should not be limited to answering the immediate referral question. Imaging reports should include structured secondary findings when clinically relevant and should link these findings to recommended follow-up pathways. For example, a CT scan performed for abdominal pain may also identify severe vascular calcification, low muscle mass, fatty liver, or vertebral compression fracture. These findings may indicate cardiovascular risk, frailty, metabolic syndrome, or osteoporosis, even if they are unrelated to the presenting complaint. Radiology integration requires structured reporting, standardized terminology, linkage of imaging findings to laboratory and clinical data, and communication pathways to family medicine and relevant specialties. Imaging-derived markers should be interpreted in context, avoiding unnecessary alarm while ensuring that clinically important incidental and opportunistic findings are not ignored.

5.3 Laboratory Medicine Subsection: Role, Contribution, Relevance, and Integration

Laboratory medicine provides one of the most sensitive windows into early disease biology. Many chronic and acute conditions produce measurable laboratory changes before symptoms occur. Longitudinal trends in hemoglobin, white blood cell count, platelets, creatinine, estimated glomerular filtration rate, urine albumin, liver enzymes, bilirubin, albumin, glucose, hemoglobin A1c, lipids, inflammatory markers, thyroid function, coagulation parameters, and electrolytes may reveal early deterioration [12–14].

The predictive value of laboratory data is enhanced when results are analyzed longitudinally rather than as isolated normal or abnormal values. A creatinine value may remain within the reference range while still representing a clinically important decline from the patient's baseline. Similarly, progressive microcytosis may precede symptomatic anemia, rising hemoglobin A1c may precede diabetes complications, and increasing liver enzymes may indicate early metabolic or drug-induced liver injury.

Within the proposed framework, laboratory data should be standardized by test codes, units, reference ranges, specimen type, and collection time. Laboratory trends should be connected to radiology, family medicine, and administrative data. For example, iron deficiency anemia combined with missed colorectal screening and gastrointestinal symptoms should trigger endoscopic evaluation. Declining renal function combined with diabetes, hypertension, and repeated emergency attendance should trigger nephrology risk management and medication review.

5.4 Endoscopy Subsection: Role, Contribution, Relevance, and Integration

Endoscopy contributes direct visual assessment of mucosal disease and is particularly important for the prevention and early detection of gastrointestinal cancer, inflammatory bowel disease, bleeding disorders, and structural lesions. Colonoscopy allows identification and

removal of premalignant polyps, while upper gastrointestinal endoscopy can detect esophagitis, Barrett's esophagus, peptic ulcer disease, malignancy, varices, and bleeding sources [15–17].

In conventional care, endoscopy is often performed after symptoms, positive screening tests, anemia, bleeding, weight loss, or abnormal imaging. In a predictive framework, endoscopy data should be integrated with family history, laboratory trends, stool testing, medication exposure, radiology findings, pathology results, and administrative follow-up. Structured endoscopy reporting should include indication, bowel preparation quality, anatomical extent, lesion morphology, size, location, intervention, histopathology linkage, complications, and recommended surveillance interval.

Endoscopy integration is particularly important for closing the loop after abnormal results. A positive stool test, unexplained iron deficiency anemia, suspicious imaging finding, or high-risk family history should trigger referral tracking. Administrative data can identify missed appointments or delayed procedures. Family medicine can coordinate counseling and follow-up. Laboratory data can monitor anemia or inflammation. This integration reduces the risk that high-risk patients are lost between screening, diagnostic confirmation, and surveillance.

5.5 Family Medicine Subsection: Role, Contribution, Relevance, and Integration

Family medicine provides the longitudinal foundation of predictive healthcare. Primary care clinicians maintain continuity across age, disease stages, family history, lifestyle, medication use, vaccination, screening, social context, and chronic disease management [18–20]. Unlike hospital-based specialties, family medicine often observes risk accumulation over time, including obesity, smoking, sedentary behavior, hypertension, diabetes, dyslipidemia, depression, polypharmacy, occupational exposure, poor adherence, and social vulnerability.

Within the proposed framework, family medicine acts as both a data source and an intervention hub. It provides baseline risk context and receives integrated risk outputs from radiology, laboratory, endoscopy, rehabilitation, and administrative systems. Primary care teams are well placed to initiate preventive actions such as lifestyle counseling, medication optimization, vaccination, cancer screening, cardiovascular risk management, diabetes prevention, renal protection, smoking cessation, and referral coordination. Family medicine integration requires accessible dashboards, clear risk summaries, actionable recommendations, and avoidance of excessive alert burden. Predictive outputs should be clinically interpretable and prioritized according to urgency and preventability. The family medicine role is not merely to receive alerts but to coordinate shared decision-making and continuity of care.

5.6 Rehabilitation Subsection: Role, Contribution, Relevance, and Integration

Rehabilitation data are often underused in predictive healthcare, despite their value in identifying early functional decline. Functional performance may deteriorate before formal diagnosis or hospital admission. Measures such as gait speed, balance, muscle strength, endurance, range of motion, activities of daily living, exercise tolerance, pain interference, cognitive-motor performance, and falls history provide clinically meaningful indicators of frailty, disability risk, postoperative recovery, neurological impairment, cardiopulmonary limitation, and musculoskeletal decline [21–23].

Within the proposed framework, rehabilitation data should be integrated with imaging markers such as sarcopenia or degenerative disease, laboratory markers such as inflammation or malnutrition, family medicine context such as chronic disease burden, and administrative indicators such as repeated falls-related visits or prolonged hospitalization. This integration can identify patients who may benefit from early physiotherapy, occupational therapy, nutrition support, home safety assessment, assistive

devices, exercise prescription, or multidisciplinary geriatric assessment. Rehabilitation integration also supports outcome prediction after acute events such as stroke, fracture, surgery, critical illness, and cardiac disease. Functional trajectories can help predict discharge needs, readmission risk, caregiver burden, and long-term independence. Therefore, rehabilitation should be viewed not only as a treatment service after disability occurs but also as an early warning system for preventable decline.

5.7 Administrative Data Subsection: Role, Contribution, Relevance, and Integration

Administrative data include admissions, emergency visits, outpatient attendance, appointment cancellations, missed visits, length of stay, discharge destination, readmissions, procedures, diagnostic codes, billing claims, medication dispensing, insurance status, cost, and resource utilization. Although originally collected for operational and financial purposes, administrative data provide important predictive information about healthcare access, disease burden, care fragmentation, and system-level risk [24–26].

Within the proposed framework, administrative data identify patients who may not be visible through clinical markers alone. Frequent emergency visits, repeated missed appointments, prolonged admissions, early readmissions, multiple specialists, high medication burden, and delayed follow-up may indicate unmet clinical needs, poor care coordination, social barriers, or worsening disease. Administrative data can also support population health planning by identifying high-risk groups, service bottlenecks, inequities, and preventable utilization. Administrative data must be interpreted carefully because coding may be incomplete, delayed, or influenced by reimbursement rules. However, when combined with clinical data, administrative records provide valuable context for prioritizing case management, discharge planning, care navigation, and resource allocation.

5.8 Integrated Risk Pathway

The proposed pathway includes five clinical stages:

1. **Signal detection:** abnormal or changing data point is detected within one or more domains.
2. **Cross-domain confirmation:** the signal is compared with other data sources to determine consistency and clinical relevance.
3. **Risk stratification:** patients are categorized by severity, trajectory, and preventability.
4. **Preventive intervention:** appropriate action is initiated by the responsible clinical team.
5. **Outcome feedback:** outcomes are monitored to refine thresholds, workflows, and care pathways.

Table 2. Examples of cross-domain predictive patterns and preventive responses

Predictive pattern	Integrated data sources	Possible risk interpretation	Suggested clinical response
Iron deficiency anemia + missed colorectal screening + abdominal symptoms	Laboratory, family medicine, administrative, endoscopy	Possible occult gastrointestinal bleeding or colorectal neoplasia	Urgent endoscopy referral, follow-up tracking, patient navigation
Coronary calcification on CT + dyslipidemia + hypertension	Radiology, laboratory, family medicine	Elevated cardiovascular risk	Cardiovascular risk review, lipid-lowering therapy consideration, lifestyle intervention

Sarcopenia on CT + low albumin + slow gait speed	Radiology, laboratory, rehabilitation	Frailty, malnutrition, poor recovery risk	Nutrition assessment, rehabilitation program, falls prevention
Rising creatinine + diabetes + repeated emergency visits	Laboratory, family medicine, administrative	Progressive renal risk and care fragmentation	Renal protection pathway, medication review, nephrology referral
Fatty liver on ultrasound + obesity + elevated liver enzymes	Radiology, laboratory, family medicine	Metabolic liver disease risk	Weight management, metabolic assessment, hepatology referral when indicated
Poor exercise tolerance + repeated admissions + abnormal chest imaging	Rehabilitation, administrative, radiology	Cardiopulmonary limitation or chronic disease progression	Cardiopulmonary assessment, rehabilitation planning, specialist review

5.9 Implementation Architecture

The proposed implementation architecture includes a shared data layer, standardized terminology, longitudinal patient timeline, risk stratification dashboard, clinician review panel, preventive action library, and monitoring system. The dashboard should not replace clinical judgment. Instead, it should organize relevant information into a concise, interpretable format that supports multidisciplinary decision-making.

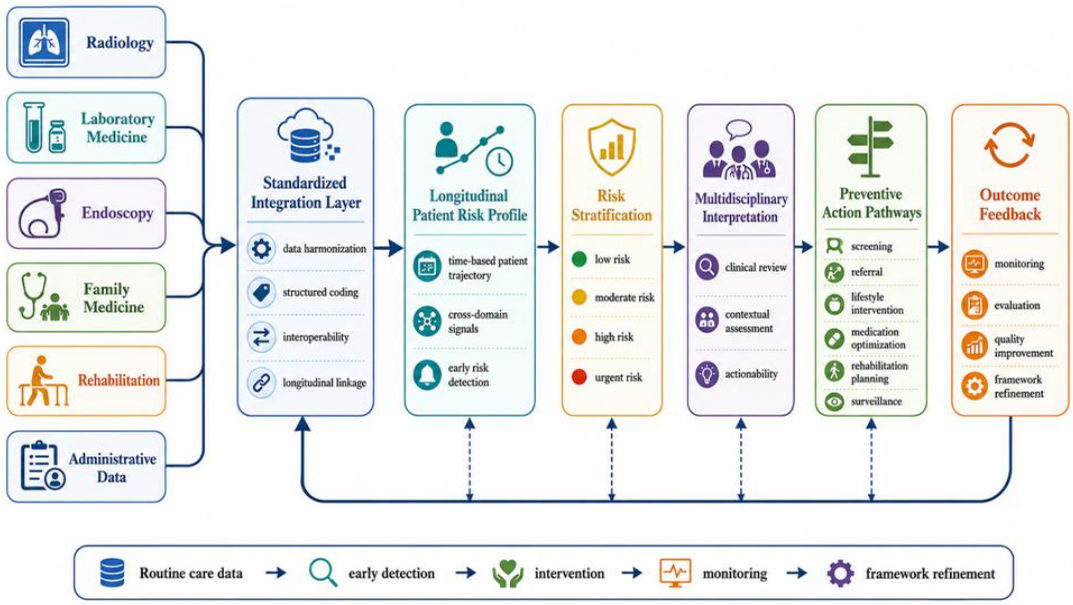

Figure 1. Proposed multisource predictive healthcare framework.

6. Discussion

The present manuscript proposes a multisource predictive healthcare framework designed to identify disease risk before symptoms or deterioration become clinically evident. The key contribution of the framework is its explicit integration of radiology, laboratory medicine, endoscopy, family medicine, rehabilitation, and administrative data into one preventive model. This approach differs from conventional care,

which commonly interprets each data stream within departmental boundaries and often responds only after symptoms develop.

6.1 Comparison with Current Practice

Current healthcare practice remains largely episode-based. A patient may undergo radiology for one complaint, laboratory testing for another, primary care review for chronic disease, endoscopy for gastrointestinal symptoms, rehabilitation after functional decline, and administrative review after hospitalization. Each encounter may be clinically appropriate, yet the overall pattern may not be recognized. The proposed model shifts the focus from isolated encounters to cumulative risk trajectories.

In conventional radiology workflows, incidental findings may be reported but not consistently linked to preventive pathways. In the proposed framework, clinically relevant imaging markers are structured and connected to primary care, laboratory values, and follow-up systems. In conventional laboratory practice, abnormal values are often interpreted individually. In the proposed framework, trends and changes from baseline are emphasized. In conventional endoscopy services, surveillance recommendations may be documented but not always tracked. In the proposed framework, endoscopy findings are linked to administrative follow-up and family medicine coordination. In conventional rehabilitation, functional assessment may occur only after disability. In the proposed framework, functional decline is treated as an early predictive signal. In conventional administrative systems, utilization data are often used for billing or reporting. In the proposed framework, utilization patterns inform clinical prevention and care coordination.

6.2 Clinical Significance of Multisource Integration

The clinical significance of multisource integration lies in its ability to detect risk patterns that may be invisible within single data streams. Many diseases develop through gradual, multisystem changes. Cardiovascular risk may appear through laboratory dyslipidemia, imaging calcification, primary care hypertension, reduced exercise tolerance, and repeated acute visits. Cancer risk may appear through family history, laboratory anemia, endoscopic lesions, imaging abnormalities, and missed follow-up. Frailty may appear through sarcopenia, malnutrition, falls, slow gait, polypharmacy, and prolonged hospitalization [21–26]. A multisource approach also supports prioritization. Health systems cannot intervene intensively for every minor abnormality. Integrated risk profiling allows teams to identify patients with converging evidence of preventable harm. This can improve clinical efficiency by directing resources toward patients most likely to benefit from early intervention.

6.3 Importance of Multidisciplinary Interpretation

Prediction alone is insufficient unless it leads to meaningful clinical action. The proposed framework therefore emphasizes multidisciplinary interpretation. Radiologists, laboratory specialists, endoscopists, family physicians, rehabilitation professionals, nurses, health informatics personnel, administrators, and quality teams each contribute unique expertise. A risk signal may be statistically notable but clinically irrelevant; alternatively, a modest abnormality may be highly important in the context of other data. Multidisciplinary review helps distinguish actionable risk from noise. Family medicine is particularly important because preventive interventions often require longitudinal follow-up, patient counseling, lifestyle modification, medication adjustment, and coordination across services. Rehabilitation professionals are essential for translating risk signals into functional prevention, particularly for older adults and patients with chronic disease. Administrative teams are essential for identifying access barriers, missed appointments, delayed procedures, and service capacity issues.

6.4 Implementation Barriers

Several barriers may limit implementation. First, data quality is variable. Missing values, inconsistent coding, free-text reporting, unit differences, duplicate records, and delayed

updates can reduce reliability. Second, interoperability remains challenging when departmental systems use different formats, terminologies, and identifiers. Third, clinicians may experience alert fatigue if risk outputs are excessive, poorly prioritized, or not clinically actionable. Fourth, governance concerns may arise regarding privacy, consent, data sharing, and accountability. Fifth, predictive systems may worsen inequities if they reflect biased access patterns or incomplete data from underserved populations [35–37]. Implementation also requires investment in infrastructure and workforce training. Health professionals must understand how risk profiles are generated, what they mean, and how to respond. The framework should be introduced gradually, beginning with high-value use cases such as colorectal cancer prevention, cardiovascular risk detection, renal deterioration, frailty prevention, and readmission reduction.

6.5 Opportunities

Despite barriers, the opportunities are substantial. First, many required data elements already exist within routine care. The challenge is not necessarily to collect more data but to connect and interpret existing data more effectively. Second, preventive care is increasingly recognized as essential for health-system sustainability. Third, structured reporting and interoperability standards are becoming more widely adopted. Fourth, multidisciplinary care models are already established in oncology, chronic disease management, geriatrics, rehabilitation, and population health. The proposed framework can build on these existing structures.

6.6 Future Research Directions

Future research should move from conceptual design to empirical evaluation. Initial studies should examine feasibility, data completeness, clinician usability, and workflow integration. Retrospective studies can identify which combinations of data predict specific outcomes. Prospective cohort studies should evaluate calibration, discrimination, clinical usefulness, equity, and preventability. Implementation studies should measure whether the framework reduces delayed diagnosis, emergency attendance, hospital admission, readmission, functional decline, and cost. Randomized or stepped-wedge designs may be used to evaluate patient-level and system-level outcomes. Future research should also investigate patient perspectives. Predictive healthcare may raise concerns about anxiety, overdiagnosis, overtreatment, privacy, and trust. Patients should be informed about how integrated data are used and how preventive recommendations are made. Equity analysis is also essential to ensure that prediction improves care for underserved groups rather than reinforcing existing disparities.

Table 3. Comparison between conventional care and the proposed multisource predictive framework

Dimension	Conventional care	Proposed framework
Trigger for action	Symptoms, abnormal single test, acute presentation	Combined risk signals before symptoms or deterioration
Data structure	Department-specific and encounter-based	Integrated, longitudinal, patient-centered
Clinical focus	Diagnosis and treatment after presentation	Early detection, prevention, and risk modification
Radiology role	Immediate diagnostic question	Imaging biomarkers and structured preventive findings

Laboratory role	Single-result interpretation	Longitudinal trend detection and biochemical risk profiling
Endoscopy role	Diagnostic or surveillance procedure	Integrated gastrointestinal risk pathway
Family medicine role	Chronic care and first contact	Central coordination of preventive action
Rehabilitation role	Post-event recovery	Early functional decline detection and disability prevention
Administrative role	Billing, reporting, utilization records	Access-risk, readmission-risk, and resource-planning intelligence
Evaluation	Process and outcome measures within departments	Cross-domain outcomes, prevention metrics, equity, and cost-effectiveness

7. Strengths and Limitations

7.1 Strengths

The proposed framework has several strengths. First, it reflects real-world clinical reasoning by integrating multiple data sources rather than relying on a single marker. Second, it includes both clinical and non-clinical domains, acknowledging that risk is shaped by biology, function, behavior, access, and healthcare utilization. Third, it explicitly defines the role of six major specialties and data domains. Fourth, it emphasizes preventive action rather than prediction alone. Fifth, it is adaptable to different healthcare settings because it can begin with available data and expand progressively. The framework also supports population health planning. By identifying high-risk groups, missed follow-up, service delays, and preventable utilization, it may help administrators allocate resources more effectively. Furthermore, the inclusion of rehabilitation data broadens prediction beyond disease diagnosis to include functional outcomes, independence, and quality of life.

7.2 Limitations

The manuscript is conceptual and does not present empirical validation. Therefore, the proposed framework should not be interpreted as a proven clinical intervention. Its performance will depend on data quality, local infrastructure, patient population, clinical workflows, and governance. Another limitation is that integrated systems may increase workload if not carefully designed. Excessive alerts, unclear responsibility, or poorly defined action pathways could reduce clinician acceptance. There is also a risk of overdiagnosis and overtreatment. Detecting risk before symptoms can be beneficial, but not every early abnormality requires intervention. The framework must therefore prioritize clinically meaningful and modifiable risk. Finally, multisource prediction may be affected by inequitable data availability. Patients with poor access to care may have fewer records, which could lead to under-recognition of risk unless equity safeguards are built into the model.

8. Clinical, Practical, and Public Health Implications

The proposed framework has important clinical implications. For individual patients, it may enable earlier detection of disease risk, more timely referral, better chronic disease management, and prevention of avoidable complications. For clinicians, it may provide a more complete view of patient risk by connecting data that are currently dispersed across systems. For healthcare organizations, it may improve care coordination, reduce duplication, support discharge planning, and identify high-risk populations. From a public

health perspective, the framework can support screening programs, chronic disease prevention, frailty management, cancer surveillance, and health equity monitoring. Administrative data can identify populations with low screening uptake, high emergency utilization, or delayed follow-up. Family medicine can deliver community-based preventive interventions. Radiology, laboratory medicine, endoscopy, and rehabilitation can provide objective markers of risk and response. The framework may also support value-based healthcare by shifting resources toward early intervention. Preventing advanced disease, disability, and hospitalization may improve outcomes while reducing long-term costs. However, cost-effectiveness must be tested empirically, as implementation requires investment in infrastructure, workforce training, governance, and evaluation.

9. Recommendations

The authors propose the following recommendations for healthcare institutions seeking to develop multisource predictive healthcare systems:

1. Establish a multidisciplinary governance committee including clinical, technical, ethical, administrative, and patient representatives.
2. Begin with high-priority use cases where early intervention is clearly beneficial, such as cardiovascular risk, colorectal cancer prevention, renal deterioration, frailty, and readmission risk.
3. Standardize data elements using accepted clinical terminology and interoperability standards.
4. Develop structured reporting templates for radiology, endoscopy, rehabilitation, and laboratory trend interpretation.
5. Link risk signals to clear clinical action pathways rather than passive alerts.
6. Ensure that family medicine and primary care teams are central to preventive follow-up.
7. Include rehabilitation measures in early risk assessment, especially for older adults and patients with chronic disease.
8. Use administrative data to identify missed appointments, delayed follow-up, frequent utilization, and access barriers.
9. Evaluate predictive performance, clinical usefulness, workflow burden, equity, and patient outcomes.
10. Conduct prospective validation before broad deployment.

10. Conclusion

The present manuscript proposes a multisource predictive healthcare framework for identifying risk before symptoms or clinical deterioration occur. By integrating radiology, laboratory medicine, endoscopy, family medicine, rehabilitation, and administrative data, the framework aims to transform fragmented healthcare information into coordinated preventive action. The model emphasizes longitudinal risk profiling, multidisciplinary interpretation, structured data standards, preventive pathways, governance, and continuous evaluation.

Compared with conventional symptom-driven care, the proposed approach may support earlier diagnosis, improved chronic disease prevention, better functional outcomes, reduced hospital utilization, and more efficient public health planning. Nevertheless, implementation requires careful attention to data quality, interoperability, ethics, clinician workflow, patient trust, and external validation. Future research should test the framework prospectively and determine its impact on patient outcomes, health equity, cost-effectiveness, and real-world feasibility.

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