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## Doctoral Thesis

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Prepared by **Nada Zendaoui**

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# Intelligent System for Telemonitoring Healthcare in Pandemic Situations

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Publicly defended on **25/04/2026**, in the presence of the jury composed of:

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technical assistance, shared knowledge, or simple words of motivation, each of you has contributed a meaningful part to the completion of this thesis.

O Allah, send Your blessings upon Your noble Messenger, his family, and his companions, and bless us in our endeavors.

# Dedication

I dedicate this doctoral work with deep love and heartfelt gratitude to:

My parents, my pillars of strength and my greatest source of inspiration. You have always encouraged me to give my best, supported me unconditionally, and surrounded me with love and faith. I pray to the Almighty to bless you with health, happiness, and long life. This success belongs as much to you as it does to me.

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# ملخص

كشفت جائحة كوفيد-١٩ عن محدودية الأنظمة التقليدية للرعاية الصحية، خاصة فيما يتعلق بضمان استمرارية المتابعة الطبية في الظروف الحرجة. تهدف هذه الأطروحة إلى معالجة هذه الإشكالية من خلال اقتراح نظام ذكي قابل للتفسير وقابل للتعميم لمتابعة المرضى عن بعد على المدى الطويل ضمن بيئات صحية واسعة النطاق.

ينطلق هذا العمل من تحليل معمّق لنماذج المتابعة الطبية عن بُعد، وأنظمة التتبع الصحي الذكي، واستراتيجيات إدارة الأزمات الصحية، مع إبراز أهم النقائص، وعلى رأسها غياب المتابعة المستمرة والشخصية للفئات الأكثر هشاشة. وفي هذا السياق، تم تصميم بنية شاملة تُعرف بـ AI-LMS مخصصة للمتابعة الطبية طويلة الأمد. وتدمج هذه البنية عدة مكونات متكاملة، من بينها AI-RiskX، وهو نموذج تعلم عميق قابل للتفسير يجمع بين شبكات CNN وLSTM وتقنية SHAP، ويهدف إلى تصنيف المخاطر والكشف المبكر عن الحالات الحرجة، بالإضافة إلى NS-Assist، وهو نظام دعم قرار قائم على المعرفة ومطبق في مجال أمراض الكلى لدى الأطفال. ويبرز هذا التنظيم الطابع المعياري وقابلية التكيف للبنية المقترحة مع مختلف السياقات السريرية.

تشكل هذه المنظومة منصة متكاملة تجمع بين التحليل المعتمد على البيانات، وقابلية التفسير، والاستدلال السريري. وتظهر النتائج أن اعتماد أنظمة التتبع الصحي الذكي القائمة على الذكاء الاصطناعي القابل للتفسير يسهم في تحسين استمرارية الرعاية، وتعزيز الثقة بين المريض والطبيب، وزيادة مرونة الأنظمة الصحية. وبذلك، تمثل هذه الأطروحة مساهمة في تطوير جيل جديد من الأنظمة الصحية الذكية، القابلة للتفسير، والأخلاقية، والقابلة للتكيف مع مختلف السياقات الطبية.

**الكلمات المفتاحية**: الذكاء الاصطناعي؛ المتابعة الطبية عن بُعد؛ التتبع الصحي الذكي؛ إنترنت الأشياء الطبية؛ الذكاء الاصطناعي القابل للتفسير؛ إدارة الأوبئة؛ تصنيف المخاطر؛ صحة الأطفال؛ نظم دعم القرار.

# Abstract

The COVID-19 pandemic has revealed critical weaknesses in global healthcare systems, particularly in their ability to ensure continuity of patient care under emergency conditions. This thesis addresses this challenge by proposing an intelligent, explainable, and generalizable framework for long-term remote patient monitoring in large-scale healthcare environments. Although COVID-19 serves as the primary case study, the proposed approach is designed to support a wide range of health monitoring scenarios requiring resilient and connected infrastructures.

This research begins with an in-depth analysis of telemedicine models, intelligent healthcare systems, and health crisis management strategies, highlighting major limitations most notably the lack of continuous and personalized long-term monitoring for vulnerable populations. Based on these findings, a global architecture, **AI-LMS**, dedicated to long-term patient monitoring, is proposed. This architecture integrates several complementary components, including **AI-RiskX**, an explainable deep learning model combining CNN and LSTM architectures with SHAP-based analysis for risk stratification and early detection of critical conditions, as well as **NS-Assist**, a knowledge-based decision support system applied to pediatric nephrotic syndrome, demonstrating the practical applicability of the proposed framework in real-world clinical settings.

Together, these components form a unified ecosystem that integrates data-driven intelligence, explainability, and clinical reasoning. The results demonstrate that the integration of explainable AI-driven remote monitoring systems can improve continuity of care, strengthen trust between patients and clinicians, and enhance the resilience of healthcare systems. This thesis thus contributes to the development of a new generation of intelligent healthcare systems that are explainable, ethical, and adaptable to diverse clinical contexts.



***Keywords:*** *Artificial Intelligence; Remote Patient Monitoring; Internet of Medical Things; Explainable AI; Pandemic Management; Risk Stratification; Pediatric Healthcare; Decision Support Systems.*

# Résumé

La pandémie de COVID-19 a mis en évidence les limites des systèmes de santé traditionnels, notamment en matière de continuité du suivi médical dans des contextes critiques. Cette thèse vise à répondre à cette problématique en proposant un système intelligent, explicable et généralisable, dédié au suivi médical à distance des patients sur le long terme dans des environnements de santé à grande échelle.

Ce travail repose sur une analyse approfondie des approches de suivi médical à distance, des systèmes de télésurveillance médicale et des stratégies de gestion des crises sanitaires, tout en mettant en évidence leurs principales limites, notamment l'absence d'un suivi continu et personnalisé pour les populations les plus vulnérables. Dans ce cadre, une architecture globale, **AI-LMS**, dédiée au suivi médical à long terme, a été conçue. Cette architecture intègre plusieurs composantes complémentaires, notamment **AI-RiskX**, un modèle d'apprentissage profond explicable combinant des réseaux CNN et LSTM ainsi que la méthode SHAP, permettant la classification des risques et la détection précoce des situations critiques, ainsi que **NS-Assist**, un système d'aide à la décision basé sur les connaissances, appliqué au domaine des maladies rénales pédiatriques. Cette organisation met en évidence la modularité et la capacité d'adaptation de l'architecture proposée à des contextes cliniques variés.

L'ensemble constitue un echosysteme intégrée combinant analyse de données, explicabilité et raisonnement clinique. Les résultats montrent que l'intégration de systèmes intelligents de télésurveillance médicale fondés sur une intelligence artificielle explicable permet d'améliorer la continuité des soins, de renforcer la confiance entre le patient et le médecin et d'accroître la résilience des systèmes de santé. Ainsi, cette thèse contribue au développement d'une nouvelle génération de systèmes de santé intelligents, explicables, éthiques et adaptables à divers contextes médicaux.

**Mots-clés :** intelligence artificielle ; suivi médical à distance ; télésurveillance médicale ; Internet des objets médicaux ; intelligence artificielle explicable ; gestion des pandémies ; classification des risques ; santé pédiatrique ; systèmes d'aide à la décision.

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# List of Abbreviations

**Acc.**: Accuracy

**Adam**: Adaptive Moment Estimation

**AI**: Artificial Intelligence

**AI-LMS**: An AI-Based Long-Term Monitoring System for Patients in Pandemics

**AI-RiskX**: An Explainable Deep Learning approach for Identifying At-Risk patients during Pandemics

**AKI**: Acute Kidney Injury

**ANN**: Artificial Neural Network

**AUC**: Area Under the Curve

**BiLSTM**: Bidirectional Long Short-Term Memory

**BLE**: Bluetooth Low Energy

**BMI**: Body Mass Index

**CDSS**: Clinical Decision Support System

**CI**: Confidence Interval

**CKD**: Chronic Kidney Disease

**CNN**: Convolutional Neural Network

**CNN-LSTM**: Hybrid CNN–LSTM Model

**COVID-19**: Coronavirus Disease 2019

**CT-Scan**: Computed Tomography Scan

**DCNN**: Deep Convolutional Neural Network

**DL**: Deep Learning

**DSS**: Decision Support System

**EHR**: Electronic Health Record

**EMR**: Electronic Medical Record

**ECG**: Electrocardiogram

**F1**: F1-Score

**FHIR**: Fast Healthcare Interoperability Resources

**FPR**: False Positive Rate

**GDPR**: General Data Protection Regulation

**HIPAA**: Health Insurance Portability and Accountability Act

**HL7**: Health Level Seven

**ICD-10**: International Classification of Diseases (10th Revision)

**INS**: Idiopathic Nephrotic Syndrome

**IoMT**: Internet of Medical Things

**IoT**: Internet of Things

**k-NN**: k-Nearest Neighbors

**LIME**: Local Interpretable Model-Agnostic Explanations

**LSTM**: Long Short-Term Memory

**MCC**: Mobile Cloud Computing

**ML**: Machine Learning

**NLP**: Natural Language Processing

**NS-Assist**: A Pediatric Decision-Support System for Remote Healthcare Management

**RF**: Random Forest

**RNN**: Recurrent Neural Network

**ROC**: Receiver Operating Characteristic

**SHAP**: SHapley Additive exPlanations

**SMOTE**: Synthetic Minority Oversampling Technique

**SNOMED CT**: Systematized Nomenclature of Medicine – Clinical Terms

**$SpO_2$**: Peripheral Capillary Oxygen Saturation

**SVM**: Support Vector Machine

**TPR**: True Positive Rate

**WBAN**: Wireless Body Area Network

**WHO**: World Health Organization

**XAI**: Explainable Artificial Intelligence

**XGBoost**: Extreme Gradient Boosting

# General Introduction

Over the past decades, the world has witnessed a succession of health emergencies ranging from the 2003 SARS outbreak to the 2014 Ebola epidemic and, most recently, the COVID-19 pandemic that have tested the resilience and adaptability of global healthcare systems. Among these, the COVID-19 crisis stands as the most disruptive event of the 21$^{st}$ century, exposing deep structural weaknesses in traditional healthcare delivery and surveillance models. Beyond its immediate human and economic toll, it has served as a turning point in how health systems are conceptualized, governed, and technologically supported. The pandemic revealed that conventional hospital-centric approaches relying heavily on in-person interactions and centralized data processing are ill-equipped to maintain continuity of care when physical access, resources, and personnel are constrained.

Far from being a singular event, COVID-19 should therefore be regarded as a case study and catalyst for rethinking healthcare resilience on a global scale. Its lessons extend to other epidemic and pandemic scenarios such as influenza, MERS, Zika, or Ebola where similar disruptions in diagnosis, monitoring, and treatment continuity may occur. The experience underscored the necessity of shifting toward more distributed, intelligent, and patient-centric models of care, capable of functioning effectively even under mobility restrictions, infrastructure disruptions, or resource scarcity.

In this evolving context, the convergence of Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) has emerged as a transformative paradigm for next-generation healthcare [1, 2]. AI enables predictive analytics, pattern recognition, and adaptive learning from large volumes of clinical and physiological data. IoMT extends this capability to the patient's environment through wearable and embedded sensors that collect continuous health signals. MCC, in turn, ensures scalability, computational efficiency, and ubiquitous access by leveraging distributed cloud resources. Together, these three technological pillars create the foundation for intelligent telemonitoring ecosystems that can identify risk, monitor health trajectories, and assist clinical decision-making in real time, while maintaining security, explainability, and interoperability [3].

However, despite these advances, an extensive review of the literature reveals persistent challenges. Many existing healthcare applications focus on isolated tasks such as disease detection, symptom prediction, or post-treatment tracking [4]. Few frameworks integrate the entire care continuum from early risk assessment to long-term supervision and adaptive decision support within a unified, intelligent, and explainable system. Furthermore, most pandemic-response technologies remain reactive and fragmented, rather than preventive and holistic. Vulnerable populations, particularly those with chronic conditions or residing in remote regions, remain underserved due to limited digital infrastructure, absence of personalized analytics, and lack of clinician-patient integration in telemonitoring systems.

These gaps highlight an urgent need for comprehensive architectures that combine clinical expertise, continuous data acquisition, and AI-driven reasoning to ensure continuity of care in both normal and crisis conditions. They also raise several overarching research questions:

- How can we design intelligent telemonitoring systems that remain robust, adaptive, and clinically meaningful across both pandemic and non-pandemic contexts?
- How can hybrid and explainable AI models be leveraged to provide transparent, reliable, and interpretable risk assessment for heterogeneous patient populations?
- What mechanisms can ensure that automated decision-support tools align with clinical reasoning, ethical principles, and real-world healthcare needs?

Motivated by these questions, this doctoral research proposes a comprehensive and generalizable framework for intelligent healthcare telemonitoring in pandemic situations. While COVID-19 serves as the principal case study, the proposed solutions are intentionally designed to be disease-agnostic, modular, and extensible, enabling adaptation to future epidemic, endemic, or chronic-care contexts. The goal is to move beyond emergency response toward resilient, proactive, and explainable healthcare systems that integrate both human and artificial intelligence in a complementary manner.

The main objective of this thesis is to design and implement an intelligent telemonitoring architecture capable of detecting, classifying, and continuously supervising at-risk patients through hybrid AI and knowledge-driven approaches.

To achieve this objective, this thesis makes the following key contributions. First, it proposes **AI-LMS (AI-based Long-Term Monitoring System)**, a distributed and modular architecture that establishes the conceptual and technical foundations for resilient healthcare management by integrating the Internet of Medical Things (IoMT), Mobile Cloud Computing (MCC), and Artificial Intelligence (AI) for real-time monitoring. Second, it develops

**AI-RiskX**, an explainable deep learning subsystem dedicated to identifying, classifying, and interpreting multidisease risk profiles based on heterogeneous clinical and demographic data. Third, it introduces **NS-Assist**, a knowledge-based decision-support and telemonitoring system applied to pediatric nephrology, demonstrating the practical implementation of the proposed framework in a sensitive clinical domain. These components together form a coherent and interoperable ecosystem.

The thesis is organized into two major parts that reflect both the theoretical and practical dimensions of the research.

The **first part** establishes the scientific and technological foundations through three chapters:

1. *Pandemic Management:* outlines the epidemiological principles, response strategies, and governance mechanisms underpinning global health preparedness.

2. *Telemonitoring in Healthcare:* explores enabling technologies such as AI, IoMT, MCC, and Explainable AI (XAI), and discusses their convergence in healthcare systems.

3. *Review of Related Research:* analyzes state-of-the-art studies on intelligent telemonitoring, identifying their strengths, limitations, and open research challenges.

The **second part** presents the core contributions, structured around the progressive implementation of the proposed framework:

1. *AI-LMS: An AI-Based Long-Term Monitoring System for Patients in Pandemics:* the overarching architecture that orchestrates distributed intelligence for pandemic-resilient healthcare supervision.

2. *AI-RiskX: An Explainable Deep Learning Approach for Identifying At-Risk Patients during Pandemics:* a deep learning-based subsystem for multidisease risk detection, incorporating explainability mechanisms to enhance clinical trust and transparency.

3. *Evaluation and Results of AI-RiskX:* a comprehensive experimental validation, including performance analysis, comparative evaluation, and implementation through an interactive web-based interface.

4. *NS-Assist: A Pediatric Decision-Support System for Remote Healthcare Management:* an applied case study demonstrating the integration of rule-based reasoning and IoMT data within pediatric nephrology.

Through these contributions, the thesis aims to establish the conceptual, methodological, and technological foundations of a new generation of AI-enabled, explainable, and ethically aligned telemonitoring systems. The proposed approach seeks to bridge the gap between academic research and clinical practice by promoting transparency, scalability, and interoperability—key requirements for future healthcare systems.

Finally, this work advocates for a paradigm shift in digital health: from reactive disease management to proactive, intelligent, and equitable healthcare. By uniting artificial intelligence, connected technologies, and human expertise within a unified framework, this research contributes to the development of sustainable healthcare infrastructures capable of withstanding future global health crises while ensuring continuity, personalization, and trust in patient care.

# Part I: Theoretical and Foundations

# Chapter 1

# Pandemic Management

## 1.1 Introduction

Pandemics represent critical junctures in human development, revealing vulnerabilities not only in biomedical systems but also in governance, communication, and technological infrastructures. From the Black Death in the fourteenth century to COVID-19 in the twenty-first, these global crises have reshaped public-health paradigms and raised pressing questions about the adaptive capacity of societies and their healthcare systems.

Beyond their medical dimension, pandemics are multidimensional phenomena that disrupt social, economic, and political structures while accelerating innovation and cooperation. Each outbreak emerges as both a tragedy and a catalyst for transformation, exposing the dynamic interplay between science, policy, and society.

The management of pandemics requires an integrated, evidence-based approach that extends beyond clinical care. It encompasses surveillance, risk communication, governance, and ethical decision-making. As emphasized by the World Health Organization (WHO), preparedness involves a continuous cycle of prevention, detection, response, and recoveryanchored in transparency, solidarity, and public trust [127]. This process demands both institutional resilience and community engagement.

The COVID-19 crisis highlighted the strengths and weaknesses of global health systems. Countries with proactive surveillance, timely interventions, and digital monitoring tools contained transmission more effectively, while those with fragmented governance and delayed responses faced aggravated outcomes. These contrasts underscore the need for sustained investment in health security, coordinated governance, and international collaboration.

This chapter traces the conceptual and historical evolution of Pandemic Management. It

reviews key frameworks, governance mechanisms, and comparative strategies adopted worldwide, emphasizing the growing role of digital health and intelligent telemonitoring systems. These developments are situated within a broader socio-technical and ethical context, laying the conceptual foundation for the intelligent telemonitoring and decision-support frameworks presented in the subsequent chapters.

## 1.2 Foundations of Pandemics

According to the World Health Organization (WHO), "a pandemic happens when a new disease spreads globally and impacts a large number of people across several regions and continents" [128]. It represents the highest level of infectious-disease propagation within the epidemiological continuum, which also includes the *endemic* and *epidemic* stages [5]. An endemic disease remains stable within a specific population or region, while an epidemic refers to an unexpected rise in incidence within a defined area. When such an epidemic crosses international borders and demonstrates sustained human-to-human transmission, it escalates into a pandemic [6].

### 1.2.1 Historical Perspective

Historically, pandemics have profoundly shaped human societies. The $14^{th}$-century **Bubonic Plague (Black Death)** eradicated nearly one-third of Europe's population, introducing early public-health measures such as isolation and quarantine. The **1918 Spanish Influenza** caused an estimated 50 million deaths globally and led to systematic disease surveillance and international cooperation in health governance [7]. The **1957 Asian Flu** and the **1968 Hong Kong Flu** further illustrated the accelerating effects of air travel and globalization on disease dissemination [8].

In the $21^{st}$ century, successive outbreaksincluding **SARS-CoV (2003)**, **H1N1 (2009)**, **Ebola (2014–2016)**, and most recently **COVID-19 (2019–2023)**have highlighted the need for coordinated global preparedness. Following the 2003 SARS crisis, China enacted the *Regulations on Preparedness for the Response to Emergent Public Health Hazards*, establishing an institutional model later strengthened during COVID-19 [9].

The historical trajectory demonstrates a clear shift from reactive containment to proactive prevention, increasingly supported by digital surveillance and data-driven modeling. Table 1.1 summarizes the major pandemics and their impacts, whereas Figure 1.1 depicts their chronological evolution from the Antonine Plague to COVID-19, illustrating the cyclical

nature and increasing frequency of global outbreaks. Together, these historical patterns show how pandemics have repeatedly tested healthcare systems and shaped the evolution of global health governance. They also underscore the accelerating role of technological innovation in improving disease surveillance, coordination, and preparedness.

Table 1.1: Major pandemics and their global impact. Source: Adapted from WHO (2023), CDC (2022).

| **Pandemic** | **Period** | **Key Impacts** |
|---|---|---|
| Black Death | 14th century | Killed about one-third of Europe's population; established early isolation and quarantine practices. |
| Spanish Flu (Influenza A H1N1) | 1918–1919 | Caused roughly 50 million deaths worldwide; triggered modern disease surveillance and the creation of coordinated public-health systems. |
| Asian flu (H2N2) | 1957 | Spread rapidly via air travel; spurred vaccine development and WHO-led pandemic coordination. |
| Hong Kong flu (H3N2) | 1968 | Highlighted the need for continuous influenza monitoring and international data sharing. |
| SARS-CoV | 2003 | Exposed weaknesses in outbreak readiness; led to the establishment of national emergency health-regulation frameworks. |
| H1N1 (Swine flu) | 2009 | Tested the WHO alert system and raised concerns about equitable vaccine distribution. |
| Ebola virus disease | 2014–2016 | Revealed fragility of regional health systems; prompted creation of global rapid-response initiatives. |
| COVID-19 (SARS-CoV-2) | 2019–2023 | Caused worldwide disruption; accelerated adoption of digital health, telemedicine, and intelligent surveillance technologies. |

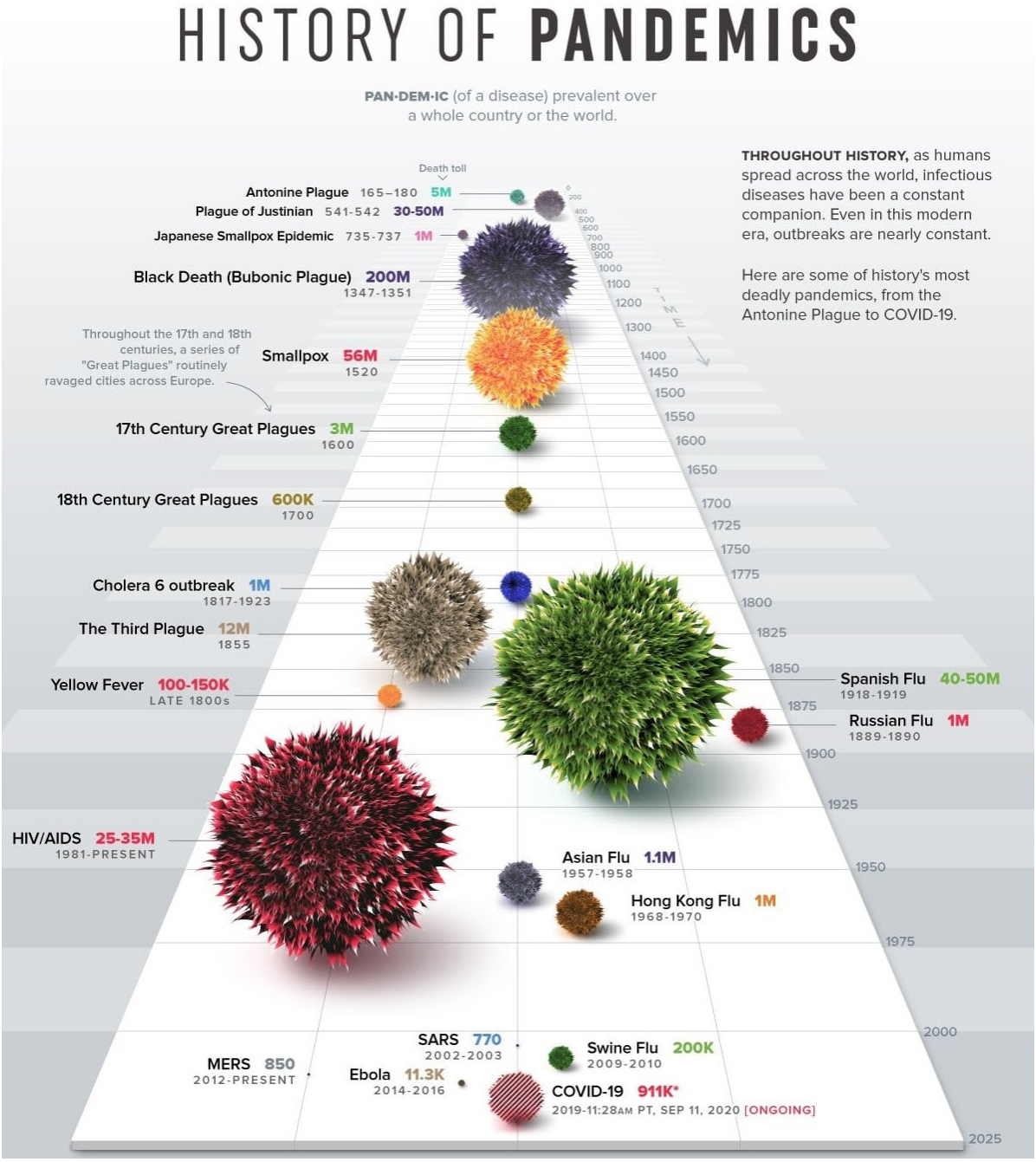



Figure 1.1: Timeline of major pandemics from the Antonine Plague to COVID-19, showing global mortality and historical recurrence. Source: Drishti IAS (2023) [130].

### 1.2.2 Pandemic Phases

The declaration of a pandemic is the responsibility of the **World Health Organization (WHO)**, based on international surveillance data and expert consultation [131]. WHO's

pandemic alert system originally developed for influenza comprises six phases that describe the progressive global spread of a novel pathogen. These are grouped into two major intervals: the **pre-pandemic interval** (Phases 1–3) and the **pandemic interval** (Phases 4–6) [133, 129]. Figure 1.2 illustrates the official *Pandemic Influenza Phases (2009)* framework defined by the World Health Organization, showing the transition from animal infections to global spread [129].

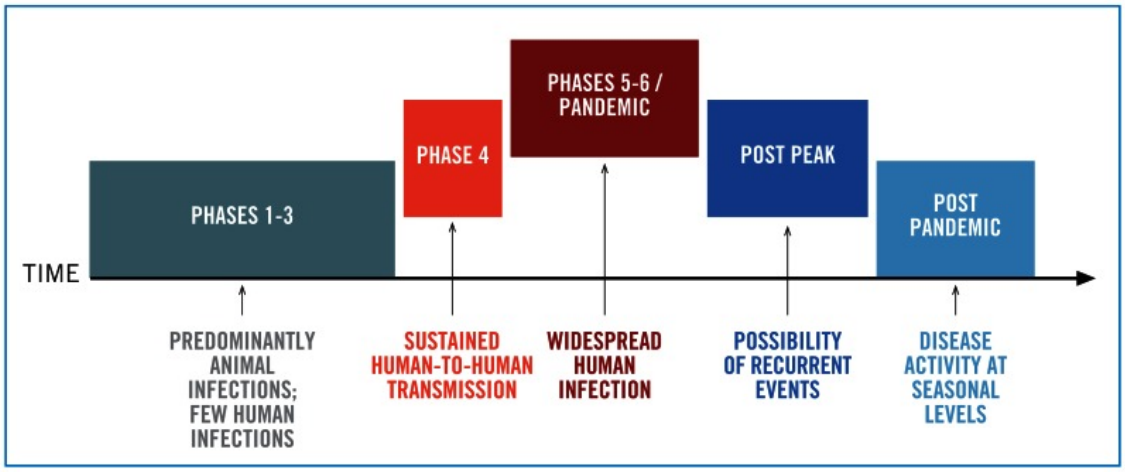



Figure 1.2: WHO Pandemic Influenza Phases (2009): six-stage framework describing the progression from animal infections to global spread [129].

### a. Pre-pandemic interval (Phases 1–3): preparedness and capacity building

1. **Phase 1:** Animal influenza viruses circulate among wild or domestic animals, posing a potential yet unrealized risk of human infection. Surveillance and risk assessment are the primary activities [129, 132].

2. **Phase 2:** An animal influenza virus causes at least one confirmed human infection, representing a potential pandemic threat. Coordination between veterinary and human health sectors intensifies [133].

3. **Phase 3:** Small clusters or isolated human cases occur following zoonotic or reassortant transmission, but without sustained community spread [129].

### b. Pandemic interval (Phases 4–6): containment, mitigation, and response

1. **Phase 4:** Sustained human-to-human transmission causes community-level outbreaks. This phase demands rapid containment measures and WHO notification [133, 129].

2. **Phase 5:** The pathogen spreads across at least two countries within one WHO region. Although most nations remain unaffected, a pandemic is imminent, prompting the activation of national mitigation plans [132].

3. **Phase 6:** Community outbreaks occur in multiple countries and in more than one WHO region, confirming a global pandemic. The focus shifts from containment to mitigation, protection of vulnerable groups, and continuity of essential services [131, 129].

**c. Actions across phases** Beyond these chronological distinctions, WHO also identifies cross-cutting actions to ensure continuous preparedness and response. During the early phases (1–3), efforts focus on developing national response plans, improving laboratory and surveillance capacity, and fostering intersectoral collaboration. In Phase 4, containment and rapid-response measures aim to delay transmission and allow time for the deployment of vaccines and therapeutics. During the advanced phases (5–6), strategies prioritize mitigation, resource allocation, and international coordination to minimize overall impact [133, 132, 131].

**d. Broader interpretation** Although originally designed for influenza, this six-phase framework underpins modern global pandemic preparedness and response strategies. Contemporary adaptations integrate social, behavioral, and technological dimensions such as misinformation dynamics, human mobility, and digital epidemiology reflecting critical lessons from COVID-19 [131]. In the aftermath of COVID-19, strengthening pandemic frameworks has become a strategic priority for global health governance. The proposed *Pandemic Prevention, Preparedness, and Response Accord* seeks to establish a legally binding mechanism for coordinated and equitable responses to future outbreaks. As of early 2025, the Accord remains under negotiation among WHO member states [134].

## 1.3 Governance Mechanisms

Recent analyses highlight the need for harmonized global strategies that go beyond reactive containment. [10] emphasized that post-COVID-19 preparedness depends on sustained global investment, transparent governance, and equitable access to vaccines, diagnostics, and therapeutics. Similarly, [11] proposed a multi-hazard framework that integrates pandemic readiness within broader disaster risk management systems, ensuring that preparedness extends across biological, environmental, and societal domains.

Another crucial component of global governance is accountability. [12] examined lessons from the COVID-19 response, underscoring the necessity of establishing resilient mechanisms for international cooperation, particularly in vaccine production and technology transfer. Their work stresses that future frameworks must guarantee global solidarity and resource-sharing, especially for low- and middle-income countries.

### 1.3.1 National and Regional Preparedness Plans

At the national level, preparedness plans operationalize global commitments into local actions. The **Australian Health Management Plan for Pandemic Influenza (AHMPPI 2019)** provides a detailed model for integrating prevention, preparedness, response, and recovery within a unified policy cycle [**?**]. Likewise, the U.S. and India have adapted WHO's guidelines to design multi-tiered response mechanisms encompassing surveillance, rapid testing, and public risk communication.

A comparative study by [13] reviewed 85 national COVID-19 preparedness strategies and revealed substantial variability in capacity, leadership, and transparency. The authors conclude that "national preparedness remains uneven and insufficiently aligned with international standards," reinforcing the urgency of stronger monitoring and accountability structures.

### 1.3.2 Key Pillars of Global Preparedness

The synthesis of recent frameworks and empirical evaluations reveals five interdependent pillars of effective pandemic preparedness:

1. **Early detection and surveillance:** Continuous monitoring of zoonotic spillovers and early warning systems using AI-enhanced analytics [11].

2. **Integrated governance:** Legal and ethical frameworks ensuring coordination between global, regional, and national agencies [10].

3. **Resource equity:** Fair allocation of vaccines, treatments, and diagnostics across socio-economic contexts [12].

4. **Community engagement:** Participatory decision-making and localized risk communication to promote behavioural compliance [14].

5. **Resilience and adaptive learning:** Continuous revision of plans through post-event evaluations and international collaboration [13].

### 1.3.3 Outlook and Future Directions

Although global preparedness capacity has advanced since 2020, systemic challenges remain. Weak global supply chains, fragmented data governance, and limited integration of socio-behavioural insights continue to impede readiness. Strengthening cross-border legal frameworks under the forthcoming WHO Pandemic Accord is essential for addressing these gaps [134]. As noted by [10], pandemic preparedness must evolve from episodic crisis response to a permanent, multidisciplinary system embedded in global governance and public trust.

## 1.4 Comparative Governance

The global response to the COVID-19 pandemic has revealed significant variation in governance structures, intervention strategies, and health-system resilience across countries. In this section, we compare three distinct national models those of China, Italy and Brazil highlighting how centralized, decentralized, and federated approaches shaped pandemic management.

### 1.4.1 China: Centralized Control and Digital Surveillance

China's Pandemic Managementwas characterized by top-down decision-making, rapid mobilisation of resources, lockdowns, and digital health codes used for movement control and contact tracing. For example, the research by Zhang et al. (2022) details how the Health Code app operated to regulate individual mobility and quarantine risk based on smartphone data. [15] Additionally, the holistic review by Bernot et al. (2022) underscores the technological, political and social dimensions of China's response. [16]

### 1.4.2 Italy: Decentralized Public-Health and Regional Response

Italy, by contrast, operates a multi-level health-system governance model where national guidelines are implemented via regional authorities. The analysis by Angelici et al. (2023) shows how regional divergence affected Italy's COVID-19 response and emphasises how coordination between central and regional governments proved challenging. [17] Another study by Natali et al. (2023) confirms that longstanding institutional dynamics persisted during the pandemic, limiting radical structural reform in Italian health governance. [18]

### 1.4.3 Brazil: Federated Coordination and Public-Health Innovation

Brazil's federated model combined federal, state and municipal efforts, leveraging digital tools and public-health campaigns in the Brazilian Ministry of Health's Emergency Operations Centre. While a comprehensive, peer-reviewed country-level study was less accessible in our verification, Brazil's model is widely acknowledged in policy reviews as a significant case of federated pandemic response. Policy commentary emphasises tele-medicine expansion and public-engagement campaigns.

### 1.4.4 Comparative Insights

From this comparison, several insights emerge:

- A centralised approach (China) can mobilise resources quickly and deploy uniform measures but may face issues of civil-liberties and data-governance transparency.
- A decentralised but regionally coordinated model (Italy) allows tailoring to local conditions and leverages regional knowledge, yet may struggle with unified national coordination in times of crisis.
- A federated system (Brazil) can harness digital innovation and public-engagement, but may be vulnerable to state-level capacity variations and inconsistent inter-governmental coordination.

These cases collectively show that Pandemic Managementis not only a matter of health-system infrastructure or funding, but is deeply influenced by governance style, legal framework, digital capability and societal trust. The need for adaptive, multi-level collaboration that integrates technology, community engagement and governance integrity is a central lesson for future preparedness frameworks.

## 1.5 Conclusion

Pandemic Managementis a complex and dynamic process that depends on the integration of public-health science, governance, and social responsibility. This chapter has explored the conceptual foundations of pandemics, their historical recurrence, and the evolution of international and national preparedness frameworks. It has also examined how different

countries such as China, Italy, and Brazil adopted distinct management models shaped by their political structures, institutional capacities, and cultural contexts.

Across all cases, several key lessons emerge. Effective pandemic response requires clear governance, timely communication, and sustained preparedness planning supported by ethical and community engagement. Centralized systems can enable rapid mobilization, while decentralized and federated models encourage local adaptation and participatory implementation. However, no single framework guarantees success; resilience ultimately depends on the alignment of institutions, policies, and societal trust.

As global health threats become increasingly complex, pandemic preparedness must evolve as a continuous and collaborative endeavor linking prevention, response, and recovery under unified international guidance. The experiences reviewed in this chapter lay the groundwork for understanding how global frameworks and national systems can better anticipate and mitigate future crises.

Building upon these insights, the next chapter, entitled **"Enabling Technologies for Intelligent and Remote Healthcare"** explores how modern healthcare systems can strengthen this preparedness through innovation, digital infrastructure, and data-driven public health.

# Chapter 2

# Telemonitoring Healthcare

## 2.1 Introduction

Building upon the governance frameworks and preparedness mechanisms discussed in Chapter 1, this chapter shifts the focus from strategic management to technological enablement. The COVID-19 crisis revealed that effective pandemic response depends not only on institutional readiness but also on the availability of robust digital infrastructures capable of sustaining care continuity under disruption. Digital and intelligent healthcare technologies such as telemedicine, telemonitoring, the Internet of Medical Things (IoMT), Mobile Cloud Computing (MCC), and Artificial Intelligence (AI) form the operational backbone that transforms preparedness plans into actionable, data-driven healthcare services.

The convergence of digital technologies and healthcare innovation has ushered in a new era of intelligent, connected, and patient-centric medical services. Over the past two decades, advances in telecommunication networks, embedded sensing, and computational intelligence have given rise to the concept of digital health an umbrella term encompassing telemedicine, telemonitoring, the Internet of Medical Things (IoMT), Mobile Cloud Computing (MCC), and Artificial Intelligence (AI). Together, these technologies have transformed healthcare delivery from reactive and location-bound to proactive, distributed, and data-driven.

The global COVID-19 pandemic accelerated this transformation, highlighting the need for resilient digital infrastructures capable of ensuring continuity of care under crisis conditions. Health systems that had invested in teleconsultation platforms, wearable monitoring devices, and AI-assisted diagnostic tools were better equipped to sustain operations, protect healthcare professionals, and maintain patient follow-up remotely. This paradigm shift demonstrated that digital healthcare is not merely a technological convenience but a strategic

imperative for healthcare resilience and preparedness.

This chapter provides a comprehensive overview of the **enabling technologies** that underpin modern intelligent healthcare ecosystems. It explores how telemedicine and telemonitoring expand clinical reach, how IoMT and MCC enable real-time connectivity and scalability, and how AI enhanced by knowledge-based reasoning and explainability enables predictive and interpretable clinical decision-making. The chapter culminates in an integrated pipeline model that connects these technologies into a coherent digital-health architecture, illustrating the full data flow from acquisition to intelligent decision support in pandemic and non-pandemic contexts.

## 2.2 Telemedicine

Telemedicine is the delivery of clinical services at a distance using information and communication technologies. It encompasses any medical act performed remotely to consult, monitor, diagnose, or treat patients without physical presence [19]. Originally deployed for isolated settings (e.g., ships, rural clinics), telemedicine has evolved into an essential pillar of modern healthcare, promoting accessibility, efficiency, and patient-centered care.

Various modalities exist, including synchronous systems (real-time video or audio consultations), asynchronous systems (store-and-forward exchanges), remote patient monitoring, and mobile-health applications [20]. Each offers distinct advantages depending on clinical requirements, infrastructure, and patient engagement. Video consultations enable interactive evaluations, while asynchronous e-consults facilitate flexible specialist review. Remote patient monitoring, often via connected devices, extends care beyond hospital walls, fostering early intervention and reducing hospitalizations.

Telemedicine reduces diagnostic and treatment delays, improves access for rural and underserved populations, lowers exposure risk for patients and clinicians, and supports continuity of care. During the COVID-19 pandemic, telemedicine rapidly expanded worldwide, allowing safe management of infected and non-infected patients alike. Virtual consultations and remote monitoring helped prevent hospital overcrowding and safeguarded healthcare workers while ensuring patients received timely guidance from home. Telemedicine has thus proven both feasible and transformative, establishing a hybrid model that integrates in-person and digital care for future healthcare delivery [21, 22].

## 2.3 Telemonitoring Systems

Telemonitoring refers to the continuous, remote acquisition and analysis of physiological and contextual patient data using connected sensors and digital platforms. It enables proactive disease management, early detection of clinical deterioration, and personalized follow-up outside traditional settings [23]. In pandemic contexts, telemonitoring minimizes physical contact while maintaining clinical oversight, demonstrating safety and scalability across multiple care pathways [24].

Typical telemonitoring architectures comprise three layers: (i) a *sensing layer* employing wearable or ambient sensors to capture vital parameters such as heart rate, temperature, and oxygen saturation ($SpO_2$); (ii) a *communication layer* that securely transmits collected data via wireless or mobile networks; and (iii) a *data-processing and application layer* that analyzes and visualizes information through dashboards to support decision-making and follow-up [25].

This layered design enables continuous, efficient monitoring beyond hospital environments, improving accessibility and responsiveness to clinical needs. Key benefits include reduced hospital burden, early intervention through near-real-time alerts, and improved patient self-management. Ongoing challenges involve device calibration, data heterogeneity, digital-access inequities, and sustained user engagement [26]. Robust telemonitoring further depends on validated signal-processing pipelines, drift-aware models, and outcome-based evaluation designs that measure clinical impact (e.g., emergency visits or admissions) rather than accuracy alone. As healthcare transitions toward hybrid, data-driven care, telemonitoring is poised to become the foundational layer for preventive and personalized services at scale.

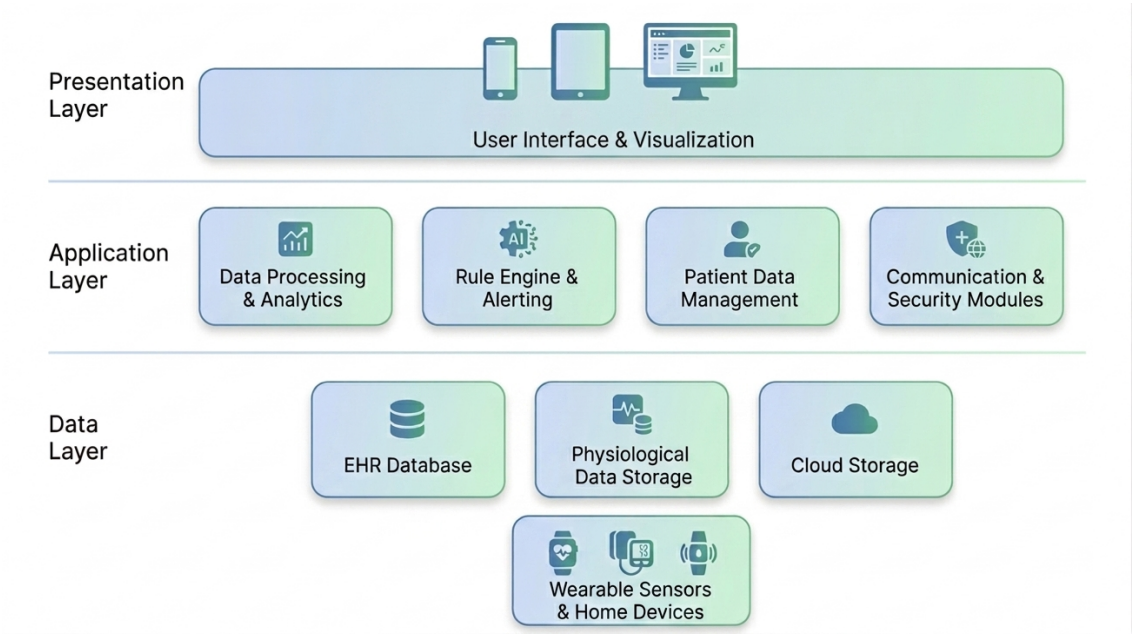



Figure 2.1: Telemonitoring architecture.

Figure 2.1 illustrates the standard three-layer architecture underpinning modern telemonitoring systems. At the base, the *data layer* aggregates information from wearable sensors, home monitoring devices, electronic health records (EHRs), and cloud repositories, forming the primary input for remote follow-up. The *application layer* performs the core analytical and operational functions, including data processing, rule-based alerting, communication security, and patient data management. At the top, the *presentation layer* provides clinicians and patients with real-time dashboards, alerts, and visualizations, ensuring intuitive interaction and informed decision-making. Together, these layers offer a scalable, interpretable, and clinically aligned foundation for continuous telemonitoring in both routine care and emergency contexts.

## 2.4 Data Acquisition and Processing

The foundation of intelligent and remote healthcare systems lies in the ability to acquire, transmit, and process health-related data efficiently and securely. Data acquisition and processing constitute the intermediary layer between sensing technologies and intelligent analytics, ensuring that collected information is reliable, consistent, and ready for clinical interpretation or AI-based decision support.

The following table 2.1 summarizes the complete data management pipeline, highlighting

the main stages and their respective roles in ensuring data reliability and integrity across intelligent healthcare systems.

Table 2.1: Overview of data management stages in intelligent healthcare systems.

| Stage | Main Tasks and Objectives |
|---|---|
| **Data Acquisition** | Collect physiological and contextual data from IoMT devices, EHRs, and medical sensors; ensure reliable transmission and calibration. |
| **Preprocessing** | Clean and filter noisy data, handle missing values, and extract relevant features for downstream analysis. |
| **Integration & Synchronization** | Align timestamps, unify data semantics using medical ontologies (HL7, FHIR, SNOMED CT), and fuse multimodal information sources. |
| **Storage & Security** | Apply encryption, anonymisation, and blockchain-based auditing to ensure privacy and compliance (e.g., HIPAA, GDPR). |
| **Preparation for Analytics** | Transform and partition datasets for ML/DL models, supporting intelligent decision-making in telemonitoring workflows. |

### 2.4.1 Data Acquisition

In intelligent healthcare ecosystems, data acquisition represents the first stage of the health monitoring pipeline. It involves the continuous collection of physiological, clinical, and contextual information from distributed sources to capture the patient's state accurately and in real time for subsequent processing and decision support.

Within this context, the **Internet of Medical Things (IoMT)** forms the technological backbone that connects sensors, medical devices, and software platforms across clinical and home environments. IoMT infrastructures enable secure and continuous data collection through wearable and implantable sensors that measure vital parameters such as heart rate, blood pressure, oxygen saturation ($SpO_2$), temperature, and glucose levels [54, 53], underscoring the shift toward sensor-driven, patient-centered connectivity in modern healthcare..

A typical IoMT-based acquisition framework operates across three interconnected layers. As mentioned earlier in the telemonitoring architecture, IoMT follows a similar layered struc-

ture (sensing, network, and application), but serves as the underlying infrastructure, whereas telemetry is limited to basic data transmission.

- the *sensing layer*, responsible for capturing physiological signals;
- the *network layer*, ensuring reliable wireless transmission via protocols such as Bluetooth Low Energy (BLE), Zigbee, Wi-Fi, or cellular networks, often structured as Wireless Body Area Networks (WBANs);
- and the *application layer*, where edge or cloud platforms aggregate and analyze the incoming data to generate actionable clinical insights [55, 56].

Beyond wearable sensing, digital health ecosystems integrate heterogeneous sources such as medical imaging, laboratory results, electronic health records (EHRs), and patient-reported outcomes, enabling a holistic and longitudinal view of patient health [25, 57]. Ensuring high data quality requires robust calibration, secure transmission mechanisms that preserve signal integrity and temporal consistency. These studies collectively highlight the importance of standardizing data flows to ensure reliability across heterogeneous health systems [30, 29].

> **Example of IoMT in pandemic monitoring:** During the COVID-19 pandemic, IoMT infrastructures proved instrumental in maintaining continuity of care while minimizing physical contact. Remote monitoring systems enabled healthcare providers to track quarantined or high-risk patients, detect early deterioration, and coordinate timely interventions [59, 58]. These experiences demonstrated IoMT's long-term value as a foundation for scalable, patient-centered, and preventive healthcare.

### 2.4.2 Data Preprocessing

Raw health data are often incomplete, noisy, or redundant due to sensor drift, transmission loss, motion artifacts, or user noncompliance. Preprocessing aims to improve data quality through systematic cleaning, filtering, and normalization before analytical or predictive modeling [26].

Key preprocessing tasks include noise filtering (e.g., smoothing, median, or Kalman filters), outlier detection through statistical thresholds, and handling missing data via interpolation or imputation. Further steps such as feature extraction computing heart-rate variability or signal energy and normalization ensure data consistency across devices and individuals.

Maintaining data quality is essential for clinical reliability. Poorly processed data can propagate errors through subsequent analytical stages, leading to misleading results or unsafe recommendations [27, 28].

### 2.4.3 Data Integration

In multi-sensor environments, synchronizing and integrating data from diverse modalities and temporal resolutions is a complex but vital process. Sensor data, laboratory tests, and medical records may follow different time stamps, sampling rates, and data formats. Effective integration requires temporal alignment, semantic mapping, and contextual harmonisation [29, 69].

Common strategies include:

- **Time alignment:** resampling or interpolating data streams to achieve consistent temporal granularity;
- **Semantic harmonisation:** mapping clinical terms to unified ontologies (e.g., HL7 FHIR, SNOMED CT, ICD-10);
- **Multi-modal fusion:** combining signals (e.g., physiological, textual, and imaging data) to produce richer representations for AI models;
- **Contextual annotation:** embedding environmental or behavioural metadata (e.g., activity level, sleep, medication timing) for contextual interpretation.

These integration steps transform fragmented information into coherent datasets suitable for downstream analytics and intelligent decision support [30, 29].

### 2.4.4 Data Storage

Healthcare data contain highly sensitive personal information, demanding strict protection and compliance with privacy regulations such as HIPAA and GDPR. Data transmission and storage mechanisms must guarantee confidentiality, integrity, and availability across distributed infrastructures [54, 62, 30].

Secure cloud-based architectures and Mobile Cloud Computing (MCC) enable scalable storage and on-demand access while maintaining strong encryption and authentication protocols. Edge computing solutions further enhance privacy by processing data locally, reducing latency, and minimizing exposure of raw patient information to external networks.

Encryption, anonymisation, and access control mechanisms, along with blockchain-based audit trails, are increasingly adopted to ensure accountability and traceability across telehealth systems. These techniques collectively safeguard patient trust and regulatory compliance in data-driven healthcare environments [30].

### 2.4.5 Data Preparation

Once data are cleaned, synchronized, and secured, they are prepared for analytical and AI-driven stages. Data preparation involves transforming preprocessed inputs into a format that can be directly interpreted by computer algorithms, selecting relevant features, and partitioning datasets for training, validation, and testing [30, 31].

Feature engineering may incorporate both statistical descriptors and domain knowledge, enabling models to capture clinically meaningful patterns. Modern data pipelines leverage automated preprocessing frameworks that integrate real-time ingestion, cleaning, and storage with cloud-based analytics and AI engines. Such end-to-end data preparation workflows enable a seamless transition from sensing to prediction, laying the groundwork for the advanced analytical techniques discussed in the following section.

## 2.5 Mobile Cloud Computing

**Mobile Cloud Computing (MCC)** represents the convergence of mobile computing and cloud technologies to extend the computational and storage capabilities of mobile devices through remote cloud infrastructures. It enables the offloading of resource-intensive tasks such as data processing, analytics, and AI inference to powerful cloud servers via wireless communication networks. By combining ubiquitous mobile connectivity with elastic cloud resources, MCC effectively overcomes device limitations related to processing power, energy consumption, and memory constraints, while also addressing latency through optimized data transmission and edge-assisted processing, which is essential for real-time monitoring applications [60, 61].

In the healthcare domain, MCC acts as a critical enabler for remote data management, real-time monitoring, and telemedicine through its integration with the **Internet of Medical Things (IoMT)**. It ensures that physiological data collected from wearable and implantable devices are continuously transmitted and analyzed on demand, supporting timely diagnosis, decision-making, and collaboration among healthcare professionals. During global health crises such as the COVID-19 pandemic, MCC infrastructures proved indispensable in sus-

taining telemedicine platforms and large-scale telemonitoring, ensuring continuity of care, real-time data sharing, and efficient management of healthcare resources [62].

## 2.6 Artificial Intelligence

**Artificial Intelligence (AI)** encompasses computational systems that emulate cognitive functions such as learning, reasoning, and decision-making. In healthcare, AI technologies transform raw clinical data into predictive and actionable insights, augmenting clinicians in disease detection, prognosis, and treatment planning [32]. Rather than serving as an abstract concept, AI now represents a practical enabler of precision medicine and large-scale telemonitoring.

### 2.6.1 Machine Learning

Machine Learning (ML), a core subset of Artificial Intelligence (AI), encompasses computational methods that enable systems to learn from data and improve task performance without explicit programming. Rather than relying solely on manually crafted rules, ML algorithms develop internal models that capture patterns and relationships from experience, adjusting their parameters to minimize predictive errors [33, 34].

ML methods are generally categorized into supervised, unsupervised, and reinforcement learning paradigms [36]. In supervised learning, models are trained on labeled datasets to perform classification or regression tasks. Typical algorithms in this category include Decision Trees, which split input space hierarchically based on feature thresholds; Support Vector Machines (SVMs), which construct optimal separating hyperplanes; Random Forests, which combine multiple decision trees to enhance generalization; k-Nearest Neighbors (k-NN), which classify instances based on proximity in feature space; and Logistic Regression, a statistical model estimating class probabilities via a logistic function [37]. Unsupervised learning, on the other hand, identifies hidden structures in unlabeled data [38], while reinforcement learning focuses on training agents through reward-based interactions with their environment [39].

In recent years, ML has played a transformative role in healthcare and public health. During global pandemics such as COVID-19, ML techniques have been instrumental in rapid screening, accurate disease prediction, efficient contact tracing, reliable forecasting, and the discovery of potential drugs and vaccines. By analyzing clinical, imaging, and demographic data, ML models have enhanced the precision and reliability of pandemic management and treatment optimization. Nevertheless, it remains essential to validate these models in real-

world environments to ensure their robustness, reliability, and ethical deployment [35]. Building upon these advances, Deep Learning (DL) has emerged as a more powerful branch of ML, capable of handling high-dimensional and unstructured data with remarkable efficiency.

### 2.6.2 Deep Learning

Within the broader field of ML, DL represents an advanced approach that leverages multilayered Artificial Neural Networks (ANNs) to analyze and learn complex patterns from large datasets [40]. These networks automatically extract and transform hierarchical features, adjusting internal parameters such as weights and biases to minimize prediction errors [34]. Unlike traditional ML algorithms that often depend on manual feature engineering, DL architectures can autonomously learn high-level abstractions from raw input data, such as images, audio, or text [41].

According to Alzubaidi et al. [42] the main types of DL architectures include Multilayer Perceptrons (MLPs), which are fully connected feedforward networks; Convolutional Neural Networks (CNNs), designed to process grid-like data such as images; Recurrent Neural Networks (RNNs), specialized for sequential data and temporal dependencies; and Recursive Neural Networks (RvNNs), which operate on hierarchical structures such as trees or graphs. Each architecture is optimized for specific data representations and learning objectives within the broader field of deep learning.

In recent years, DL models, particularly Convolutional Neural Networks (CNNs), proved instrumental in medical imaging applications, accurately detecting and classifying infection severity from CT scans (Computed Tomography scan) and identifying pneumonia-related visual markers. These advances highlight the transformative potential of DL in data-driven medical analytics, significantly enhancing diagnostic precision and clinical decision support [43].

### 2.6.3 Knowledge-Based and Symbolic AI Approaches

While data-driven Artificial Intelligence (AI) methods such as Machine Learning and Deep Learning have achieved remarkable success, symbolic and knowledge-based paradigms remain essential for interpretability, clinical trust, and alignment with medical logic. In clinical decision support, contemporary practice increasingly combines rule-based reasoning with data-driven models to obtain both adaptability and transparency [44, 45].

Expert systems emulate human specialist reasoning using an explicit **knowledge base** (facts, rules, and relations) and an **inference engine** (forward/backward chaining). Canon-

ical systems such as **MYCIN** and **INTERNIST-I**/QMR demonstrated how "IF–THEN" rules and large disease knowledge bases can deliver diagnostic recommendations with traceable justifications [44, 45, 46].

Modern clinical decision support systems (CDSS) operationalize these principles at scale, matching patient data to a computerized knowledge base to generate patient-specific assessments. Recent overviews emphasize benefits (safety, consistency), risks (alert fatigue, workflow fit), and design strategies for success, reinforcing the role of explicit knowledge in trustworthy CDSS [47, 48].

Table 2.2 synthesizes the main characteristics of data-driven and knowledge-based AI paradigms, highlighting their complementary roles in intelligent healthcare systems.

Table 2.2: Simplified comparison of main AI approaches in healthcare.

| **Approach** | **Main Idea** | **Advantages** | **Drawbacks** |
|---|---|---|---|
| **Machine Learning (ML)** | Learns patterns from data. | Works well with structured data; good for diagnosis and prediction. | Needs well-prepared data; performance drops with small datasets. |
| **Deep Learning (DL)** | Uses many neural layers to learn complex features. | Very powerful with images, signals, and text; high accuracy. | Needs large datasets and strong computing power; not easily explained. |
| **Knowledge-Based Systems** | Uses expert rules for decision-making. | Easy to understand; follows clinical logic. | Hard to update; limited flexibility. |

## 2.7 Explainable Artificial Intelligence

Traditional AI models, especially complex DL architectures, act like 'black boxes' in many cases, giving very accurate predictions without any clear insights into their decision-making process. Lack of transparency can affect further trust, wide adoption, and accountability in critical fields like healthcare. Explainable AI is a subfield aimed at making internal logic and predictions within an AI system interpretable and understandable by a human user [63].

Interpretability in healthcare is a critical enabler of safe and ethical clinical deployment: experts must understand the rationale behind an AI system's predictions to validate its re-

liability and find sources of bias or error. More transparent models build clinician trust, help shared decision-making, and support the needs of regulatory compliance [64]. Explainable systems in pandemic response are a way to make automation behind risk assessments, diagnostic outputs, and treatment suggestions truly clinically responsible [65].

Among the different existing methods, SHapley Additive exPlanations (SHAP) has gained rapid popularity. Based on the principles of cooperative game theory, SHAP attributes to each feature its Shapley value, which represents its average contribution to a model's prediction within all possible coalitions of features [66]. The simple intuition behind SHAP is that it explains how much each feature 'contributes' to moving a prediction from its base-line average output. The approach has since been extended to both local explanations describing the reasoning behind an individual prediction and a global explanation that summarizes the overall feature importance across a dataset. Its mathematical consistency and model-agnostic design makes SHAP particularly useful for sensitive domains like healthcare, where clinical trust and decision support require more sophistication [67].

The Shapley value for a model $f$ and input $x \in \mathbb{R}^M$ with $M$ features is defined as [66]:

$$\phi_i(f, x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} \left[ f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S) \right] \tag{2.1}$$

where $F$ is the set of all features, $S$ is a subset excluding $i$, and $f_S(x_S)$ is the expected model output using only features in $S$. Key properties additivity, local accuracy, and consistency ensure reliable feature attribution. Approximation techniques such as Deep SHAP are used for computational efficiency in large networks [66].

XAI has huge potential and proved to be a very important element in making AI-based medical solutions more transparent, trustworthy, and reliable espacially during the COVID-19 crisis. It played an essential role in diagnostic imaging, treatment recommendation, predictive modeling, and vaccine research by improving the interpretability of complex algorithms. This enabled clear explanations of model behavior and reasoning, hence building clinicians' confidence in automated systems, supported ethical deployment, and accelerated development of personalized and data-driven healthcare solutions [68].

## 2.8 From Data to Decisions

The integration of digital technologies across healthcare has led to the emergence of a complete end-to-end pipeline that connects patients, sensors, data infrastructures, and intelligent analytics into one coherent ecosystem. This pipeline represents the operational backbone of

intelligent and remote healthcare, where information flows seamlessly from patient interaction to clinical decision support through interconnected layers of sensing, transmission, processing, and artificial intelligence.

Figure 2.2 provides an overview of the end-to-end intelligent healthcare pipeline, illustrating the flow from telemedicine and data acquisition through IoMT and MCC, to data processing, AI-driven analytics, and explainable decision support. This integrated architecture ensures seamless interaction between patients, devices, and intelligent systems for adaptive, transparent, and patient-centered care.

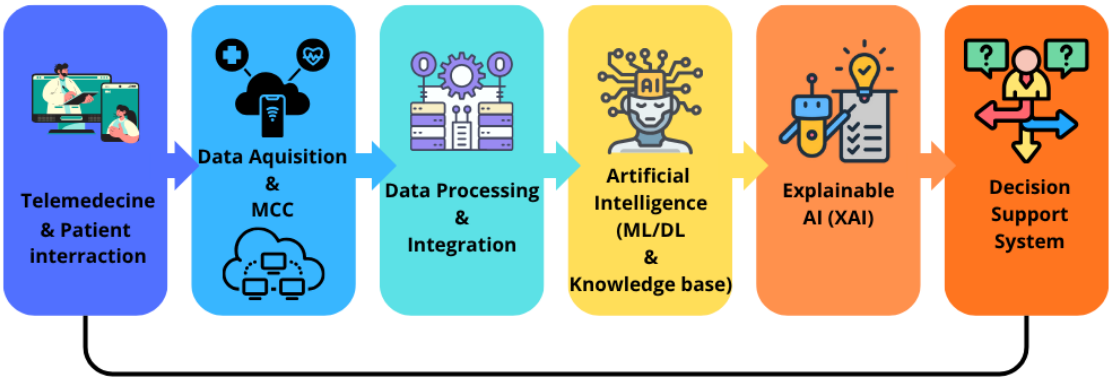



Figure 2.2: End-to-end intelligent healthcare pipeline connecting data acquisition, AI analytics, and clinical decision support.

At the initial stage, telemedicine platforms serve as the primary interface between patients and healthcare professionals, enabling remote consultation, triage, and follow-up. These interactions generate both clinical and contextual data, which are complemented by continuous physiological measurements collected through the Internet of Medical Things (IoMT). Wearable and implantable devices capture parameters such as heart rate, temperature, and oxygen saturation, transmitting them securely through Mobile Cloud Computing (MCC) infrastructures that ensure low-latency communication, scalable data storage, and ubiquitous access. Together, telemedicine and IoMT provide the sensing and connectivity foundation required for real-time monitoring and proactive care delivery.

The next stage involves data processing and intelligent analytics. Acquired signals undergo preprocessing, cleaning, and synchronization to guarantee quality and consistency be-

fore being analyzed through Artificial Intelligence (AI) methods. Machine Learning (ML) and Deep Learning (DL) models identify hidden patterns, predict disease risk, or support early diagnosis, while knowledge-based incorporate expert reasoning to ensure interpretability and alignment with clinical protocols. These intelligent layers transform raw data into actionable insights that enhance clinical precision, safety, and efficiency across telemonitoring and decision-support workflows.

Finally, the Explainable AI (XAI) layer bridges the gap between algorithmic prediction and clinical interpretation by providing transparent justifications for model outputs. Through feature attribution or rule-based explanation, clinicians can understand, validate, and trust automated recommendations. The resulting risk alerts, diagnostic suggestions, or treatment recommendations are delivered back to healthcare providers and patients through dashboards or mobile applications, closing the feedback loop and enabling continuous, adaptive, and patient-centered healthcare.

## 2.9 Conclusion

This chapter examined the core technologies underpinning intelligent and remote healthcare. The convergence of telecommunication, sensing, and computational intelligence has transformed digital health from a supportive innovation into a central pillar of modern medical practice. Telemedicine and telemonitoring extend clinical care beyond hospital walls, ensuring continuous observation, early intervention, and equitable access even during public-health emergencies.

At the infrastructural level, IoMT and MCC provide the backbone for real-time, secure, and scalable data exchange, enabling continuous capture and processing of physiological and contextual information. Artificial Intelligence through ML/DL models, knowledge-based reasoning, and Explainable AI forms the analytical core that converts this data into interpretable, actionable insights. Together, these pillars support the intelligent systems developed in this thesis and lead to the next chapter, Review of Related Research, which examines the state of telemonitoring, AI, and clinical decision-support solutions.

The next chapter, Review of Related Research, builds upon these technological foundations. It critically analyzes state-of-the-art approaches in telemonitoring, artificial intelligence, and clinical decision support, identifying current advances and research gaps that motivate the conception of the proposed systems in this thesis.

# Chapter 3

# Review of Related Research

## 3.1 Introduction

The ongoing digital transformation of healthcare has been profoundly accelerated by global health crises such as the COVID-19 pandemic. The sudden disruption of conventional care delivery models exposed major vulnerabilities in hospital-based systems and highlighted the need for intelligent, distributed, and data-driven infrastructures capable of ensuring continuity of care under emergency conditions. In this context, the convergence of Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) has emerged as a cornerstone of modern telehealth, enabling continuous monitoring, real-time disease detection, and predictive analytics that extend clinical expertise beyond traditional settings.

The principal objective of this chapter is to provide a comprehensive review of recent advances in AI-enabled healthcare systems, emphasizing their evolution from pandemic-oriented applications to more generalized, explainable, and patient-centered frameworks. This review is structured into two major parts:

- **Part I – Pandemic Intelligent Systems:** examines how AI, IoMT, and MCC were employed during the COVID-19 pandemic across five operational dimensions detection, prediction, monitoring, safety enforcement, and post-COVID rehabilitation. It highlights the rapid technological responses, their methodological diversity, and the limitations that hindered long-term sustainability.

- **Part II – AI for Disease Monitoring and Prediction:** analyzes broader developments in telemonitoring, with a focus on multidisease risk assessment, explainable AI,

and pediatric telemonitoring solutions. This section shows how research has progressively expanded from crisis-driven applications to continuous and personalized healthcare paradigms, providing the conceptual foundation for the AI-LMS, AI-RiskX, and NS-Assist frameworks proposed in this thesis.

By synthesizing both pandemic-focused and general health-monitoring research, this chapter traces the scientific progression from reactive crisis management to proactive, intelligent, and inclusive healthcare ecosystems. It also identifies persistent gaps including limited interpretability, fragmented data integration, and inadequate support for vulnerable populations that motivate the design of the multi-layered and explainable telemonitoring architectures developed in this thesis.

## 3.2 Pandemic Intelligent Systems

The COVID-19 pandemic represented an unprecedented stress test for global health infrastructures and catalyzed a technological transformation toward intelligent, data-driven healthcare. Traditional medical systems, often centralized and reactive, struggled to provide continuity of care under lockdown conditions and resource shortages. Consequently, the integration of Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) became essential to ensure scalable monitoring, early detection, and efficient public-health response. This section presents an in-depth and phase-oriented review of representative studies developed between 2020 and 2023, focusing on their methodologies, achievements, and limitations within five principal pandemic-management phases: *detection*, *prediction*, *monitoring*, *safety enforcement*, and *post-COVID rehabilitation*.

### 3.2.1 Overview and Analytical Framework

The rapid emergence of COVID-19 inspired thousands of works across medical imaging, epidemiological forecasting, IoT-based surveillance, and digital triage. While this diversity accelerated innovation, it also led to fragmentation and inconsistent evaluation practices. To organize this vast literature, studies are categorized according to their dominant functional goal:

- **Detection:** identifying infected or suspected cases using imaging, biosignals, or electronic records;

- **Prediction:** forecasting epidemic spread, patient deterioration, or healthcare-system pressure;
- **Monitoring:** enabling continuous remote supervision of vital signs and symptoms through IoMT devices;
- **Safety and Prevention:** enforcing protective measures (masking, distancing, contact tracing);
- **Post-COVID and Rehabilitation:** addressing long-term consequences and chronic sequelae.

This functional segmentation highlights how research priorities evolved from emergency detection to long-term resilience and reveals the progressive convergence of AI analytics and IoT-based sensing within the pandemic lifecycle.

### 3.2.2 Detection Phase

The detection phase received the earliest and most intensive attention, as rapid screening was vital to containment. Deep learning, particularly Convolutional Neural Networks (CNNs), dominated the landscape due to their ability to extract discriminative visual features from chest X-rays and CT scans.

Al-Rakhami et al. [75] combined CNN and Recurrent Neural Network (RNN) architectures, achieving near-perfect accuracy (99.9%) and area-under-curve (AUC) values for COVID-19 identification. Polsinelli et al. [76] proposed a lightweight SqueezeNet variant tailored for CT imaging, reaching 85.03% accuracy while optimizing computational cost. Similarly, Maria Alam et al. [80] utilized EfficientNet with extensive augmentation to attain accuracies approaching 99%. Kodi Jahnavi et al. [79] validated the robustness of classical networks such as ResNet50 and VGG19 across multiple chest-X-ray corpora, achieving 93–98.5% accuracy.

Beyond imaging, several works explored alternative modalities. Obeid et al. [77] applied Natural-Language Processing (NLP) to clinical documents, obtaining an AUC of 0.729 for text-based screening, while Jiang et al. [78] fused RGB and infrared sensors in a bidirectional-GRU model for contactless respiratory analysis (accuracy 83.69%). These innovations demonstrated that multimodal data text, images, biosignals could complement each other to enhance diagnostic reliability.

**Critical insights.** Despite impressive metrics, most detection frameworks suffered from limited dataset diversity, over-representation of specific geographic cohorts, and lack of external validation. Many relied on public datasets of modest scale (hundreds of images), which inflated accuracy yet hindered generalization. Explainable AI (XAI) methods such as Grad-CAM were sometimes appended, but their interpretability for clinicians remained superficial. Hence, while detection research demonstrated the feasibility of rapid AI triage, reproducibility and clinical trust remained unresolved.

### 3.2.3 Prediction Phase

Following initial containment, attention shifted to predictive modeling anticipating epidemic surges, hospital occupancy, and patient deterioration. Machine-learning and deep-learning time-series models became the analytic backbone of short-term forecasting.

Alazab et al. [81] proposed a Pattern-Awareness (PA) algorithm outperforming classical Long Short-Term Memory (LSTM) and ARIMA models in infection-rate prediction. Wang et al. [82] integrated demographic and environmental factors into LSTM networks, improving mean absolute percentage error by 10%. Babukarthik et al. [84] and Muhammad et al. [83] employed deep-CNN and statistical ensembles to forecast case trajectories, reporting accuracies between 94.9 and 98.8%.

Although these models offered quantitative foresight, they largely omitted behavioral and policy variables such as mobility or vaccination rates. Their limited temporal span (typically weeks) constrained long-term forecasting and adaptability to new viral variants. Few frameworks adopted transfer learning or cross-regional calibration, reducing their practical scalability.

**Critical insights.** Prediction research succeeded in establishing data-driven epidemic intelligence but exposed a dichotomy between algorithmic accuracy and socio-epidemiological realism. Future preparedness frameworks should fuse epidemiological, climatic, and mobility indicators within adaptive, explainable models capable of continuous recalibration.

### 3.2.4 Monitoring Phase

As health systems adapted to the prolonged crisis, remote monitoring emerged as a cornerstone of digital healthcare. IoMT devices and wearable sensors enabled continuous acquisition of physiological signals heart rate, oxygen saturation, temperature linked to cloud analytics for early-warning alerts.

Otoom et al. [**?**] proposed an IoT–ML framework using SVM, KNN, and Naïve Bayes classifiers for real-time COVID-19 detection, achieving 90% accuracy. El-Rashidy et al. [98] combined wearable sensors, fog computing, and CNNs for end-to-end monitoring, reporting 97.95% accuracy and 98.85% specificity. Nasser et al. [97] introduced a cognitive IoT–cloud architecture using ResNet50 on CT scans, achieving 98.6% accuracy and an F1-score of 97.87%. Jeyaraj et al. [95] developed Smart-Monitor, a DCNN-based system achieving 97.5% accuracy within 65 seconds for vital-sign analysis. Jaber et al. [99] proposed a Meta-Heuristic CNN (MHCNN) for wearable-sensor assessment with 98.76% accuracy, while Bhardwaj et al. [96] implemented an IoT monitoring platform tailored for rural clinics, demonstrating practical feasibility with limited resources.

**Critical insights.** These studies collectively illustrated the transition from static diagnostics toward continuous, personalized telemonitoring. However, interoperability across devices, data-format heterogeneity, and energy constraints at the sensor level persisted as major bottlenecks. Few systems incorporated clinician-in-the-loop feedback or adaptive thresholding, limiting clinical reliability. Moreover, security and privacy considerations especially under cloud connectivity remained underexplored.

### 3.2.5 Safety and Prevention Phase

Another research stream addressed preventive intelligence the automation of public-health measures through AI-enabled surveillance. Deep-learning vision models were deployed to monitor mask usage, physical distancing, and contact tracing.

Sahoo et al. [86] achieved 98% precision for social-distancing compliance using real-time object detection. Akib et al. [87] integrated IoT-based mask detection, contactless temperature screening, and automatic sanitizer control within a unified safety station. Garg et al. [89] combined IoT sensors with blockchain for secure contact-tracing and tamper-proof data logging. Ahmed et al. [88] compared YOLOv3 and Faster-RCNN for masked-face detection, achieving inference speeds of 0.045 s and 0.15 s, respectively.

**Critical insights.** Although technologically impressive, these systems were highly sensitive to environmental factors such as lighting and crowd density and raised ethical questions regarding mass surveillance. Balancing public safety with data privacy demands context-aware, federated approaches capable of on-device processing and anonymization.

### 3.2.6 Post-COVID and Rehabilitation Phase

As acute infection rates declined, attention shifted to post-COVID care and rehabilitation. Researchers leveraged AI to monitor residual organ dysfunction, predict complications, and support chronic disease management.

Stasenko et al. [90] analyzed electrocardiogram (ECG) data to identify "cardiospikes" characteristic of post-COVID cardiovascular anomalies, reaching 87% accuracy. Kakani et al. [91] employed CNNs for pulmonary condition classification in recovered patients (train 95–97%, test 90–95%). Shakhovska et al. [92] proposed an ensemble ML model (AUC 0.978, precision 0.924) to predict rehabilitation duration. Jha et al. [93] achieved 98% accuracy in detecting pulmonary fibrosis, while Anju Yadav et al. [94] combined CT and clinical metadata to analyze fibrosis progression.

**Critical insights.** These works demonstrated that AI can extend beyond acute crisis management to long-term telehealth and rehabilitation. Nonetheless, sample sizes were typically small, and longitudinal validation scarce. Integration with electronic medical records (EMRs) and continuous IoMT streams remains essential to generalize these approaches for chronic-care management.

Table 3.1: Representative technological approaches across COVID-19 management phases.

| **Study (Author)** | **Phase** | **Technology Used** | **Accuracy / Metrics** | **Key Contributions** |
|---|---|---|---|---|
| Al-Rakhami et al. [75] | Detection | CNN + RNN | Acc 99.9%, AUC 99.9% | Chest-X-ray classification |
| Polsinelli et al. [76] | Detection | SqueezeNet CNN | Acc 85.03% | Lightweight CT detection |
| Maria Alam et al. [80] | Detection | EfficientNet + Augmentation | Acc 98–99.9% | CT-image classification |
| Kodi Jahnavi et al. [79] | Detection | ResNet50, VGG19 | Acc 93–98.5% | Multi-dataset X-ray validation |
| Obeid et al. [77] | Detection | NLP + DL | AUC 0.729 | Clinical-text screening |
| Jiang et al. [78] | Detection | RGB–IR + biGRU-AT | Acc 83.7%, Sens 90.2% | Contactless respiration analysis |
| Alazab et al. [81] | Prediction | Pattern-Awareness (PA) vs LSTM, ARIMA | PA superior | Infection-rate forecasting |
| Wang et al. [82] | Prediction | LSTM + Demographic/Environmental data | MAPE ↓10% | Improved epidemic trend prediction |
| Babukarthik et al. [84] | Prediction | Deep CNN Ensemble | Acc 94.9–97.6% | Case trajectory forecasting |
| Muhammad et al. [83] | Prediction | Statistical Ensemble | Acc 98.8% | COVID-19 trend prediction |
| Otoom et al. [**?**] | Monitoring | IoT + ML (SVM, KNN, NB) | Acc 90% | Real-time case detection |
| El-Rashidy et al. [98] | Monitoring | CNN + Fog + Sensors | Acc 97.9%, Spec 98.8% | Wearable-based monitoring |
| Nasser et al. [97] | Monitoring | IoT + Cloud + ResNet50 | Acc 98.6%, F1 97.9% | Cognitive IoT healthcare architecture |
| Jeyaraj et al. [95] | Monitoring | DCNN + IoT | Acc 97.5% | Smart vital-sign monitoring system |
| Jaber et al. [99] | Monitoring | Meta-Heuristic CNN (MHCNN) | Acc 98.76% | Wearable-sensor health assessment |
| Bhardwaj et al. [96] | Monitoring | IoT Platform + Cloud | – | Rural telemonitoring feasibility |
| Sahoo et al. [86] | Safety | DL (Object Detection) | Prec 98%, Rec 87% | Social-distancing compliance |
| Akib et al. [87] | Safety | IoT Sensors | – | Mask + Temp + Sanitizer control |
| Garg et al. [89] | Safety | IoT + Blockchain | – | Secure contact-tracing framework |
| Ahmed et al. [88] | Safety | YOLOv3 vs Faster-RCNN | Inference 0.045–0.15 s | Masked-face detection and tracking |
| Stasenko et al. [90] | Post-COVID | ECG + ML | Acc 87% | Cardiospike anomaly detection |
| Kakani et al. [91] | Post-COVID | CNN | Train 95–97%, Test 90–95% | Pulmonary-disease classification |
| Shakhovska et al. [92] | Post-COVID | Ensemble ML | AUC 0.978, Prec 0.924 | Rehab-duration prediction |
| Jha et al. [93] | Post-COVID | DL (CT Analysis) | Acc 98% | Pulmonary fibrosis detection |
| Anju Yadav et al. [94] | Post-COVID | CT + Clinical Metadata | – | Fibrosis progression analysis |

### 3.2.7 Temporal Evolution of Research Focus

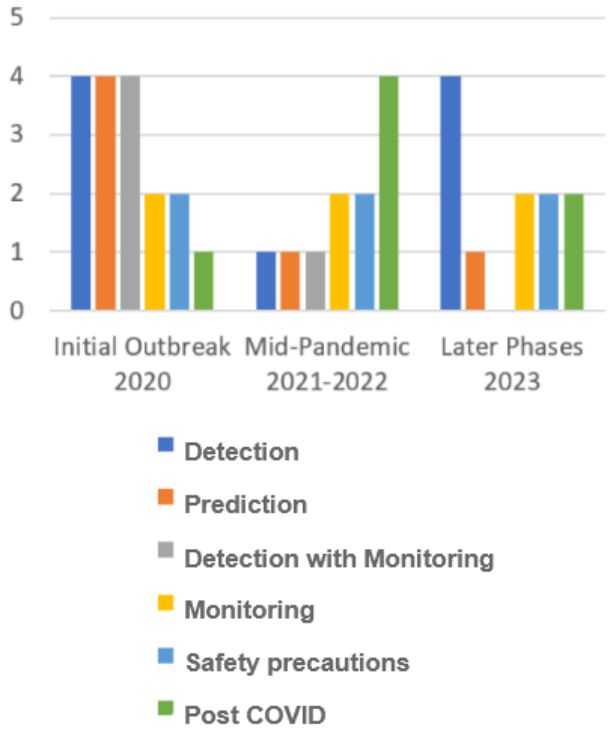



Figure 3.1: Evolution of technological focus across pandemic phases (2020–2023)

As illustrated in Figure 3.1, during the initial outbreak (2020), most works prioritized rapid detection and short-term prediction to enable mass triage and outbreak forecasting. By 2021–2022, emphasis shifted toward real-time monitoring and hybrid IoMT–MCC architectures integrating data capture, analytics, and decision support. From 2023 onward, the research landscape evolved toward post-COVID care, chronic-disease surveillance, and personalized rehabilitation. This chronological shift evidences the adaptive nature of technological responses and their convergence toward resilient, connected healthcare ecosystems.

### 3.2.8 Research Gaps

Despite the remarkable progress achieved across phases, several overarching challenges persist:

- **Data Bias and Limited Generalization:** Most models were trained on small, homogeneous datasets lacking demographic diversity, resulting in performance degradation across independent cohorts.

- **Explainability Deficit:** While Grad-CAM or SHAP visualizations were occasionally used, they seldom provided actionable clinical insights or transparent decision rationales.
- **Neglect of Vulnerable Populations:** Pediatric, geriatric, and chronically ill groups remained under-represented, limiting the societal inclusiveness of deployed solutions.
- **Ethical and Deployment Constraints:** Privacy, data governance, and interoperability across healthcare jurisdictions hindered large-scale implementation.
- **Fragmented Integration:** Few works achieved full end-to-end pipelines unifying sensing, analytics, and medical decision-support within interoperable standards.

AI, IoMT, and MCC technologies profoundly enhanced the digital response to COVID-19, demonstrating the feasibility of intelligent telemonitoring under crisis conditions. However, their fragmented deployment, limited explainability, and insufficient attention to vulnerable populations highlight the need for integrated, ethical, and transparent frameworks that ensure equitable access and continuity of care. Most reviewed systems operated as isolated components focused on rapid detection, localized monitoring, or single-disease prediction without achieving full interoperability or long-term adaptability. Furthermore, issues of data bias, privacy, and model interpretability continue to challenge their transition from experimental prototypes to clinically reliable solutions.

These observations directly motivate the second part of this chapter, which explores how the lessons learned from pandemic-specific innovations can be generalized into holistic, multi-disease, and patient-centered intelligent healthcare systems. Part II extends the discussion beyond COVID-19 by examining advances in AI-driven disease detection, risk prediction, and pediatric telemonitoring frameworks laying the conceptual foundation for the proposed AI-LMS, AI-RiskX, and NS-Assist architectures.

## 3.3 AI for Disease Monitoring and Prediction

Building upon the insights gained from the previous section on Pandemic AI Systems, research attention has progressively shifted toward the development of intelligent, explainable, and patient-centered healthcare frameworks. The pandemic revealed both the potential and the limitations of AI-, IoMT-, and MCC-based solutions while effective for rapid detection and remote monitoring, most were short-term emergency implementations lacking scalability, interpretability, and adaptability to chronic or multi-disease scenarios. These constraints

were particularly evident in addressing vulnerable populations such as the elderly and individuals with comorbidities.

Consequently, current research trends emphasize the evolution of intelligent systems toward more generalizable and sustainable architectures that support continuous telemonitoring, multi-disease risk prediction, and pediatric healthcare applications. The following section reviews major contributions within this continuum, emphasizing two interrelated dimensions:

1. Generalized AI-based risk prediction and explainable modeling across multiple diseases;
2. Pediatric and intelligent healthcare systems integrating IoMT and ethical AI principles.

This synthesis also identifies persisting gaps in detection and monitoring research such as data fragmentation, single-disease bias, and limited interpretability which continue to motivate the development of trustworthy, interoperable, and inclusive intelligent healthcare architectures.

### 3.3.1 Survey on Disease Risk Detection and Predictive Modeling Methods

While the preceding systems were effective for short-term pandemic management, they generally overlooked high-risk population profiling and explainability. Recent research has therefore extended AI toward multi-disease risk detection and interpretable predictive modeling.

#### a) Single-Disease Focus

Most existing AI healthcare models remain single-disease oriented, restricting their generalizability across comorbidities. El-Sofany et al. [100] used XGBoost with SMOTE for diabetes prediction (97.4% accuracy) but lacked demographic and interpretability dimensions. Guleria et al. [101] introduced an SVM–SHAP/LIME cardiovascular model with enhanced interpretability but limited data scale. Yilmaz et al. [102] and Prathibha et al. [103] achieved 92–97% accuracy for coronary heart and thyroid disorders, respectively, though both neglected cross-disease and population diversity. Asthma-prediction studies by Awal et al. [105] and Heris et al. [106] also faced dataset imbalance and low generalization.

Later works, such as Talukder et al. [110] and Bilal et al. [111], incorporated explainability (SHAP, LIME) within cardiovascular prediction models, achieving >98% accuracy while enhancing transparency. Despite these advances, most frameworks remain disease-specific, reinforcing the need for unified, multi-disease systems.

#### b) Deep Learning and Explainable AI (XAI) in Healthcare

Deep-learning paradigms such as CNNs and LSTMs have shown strong capabilities for feature extraction from medical data. Srinivasu et al. [112] designed a CNN–BiLSTM diabetes monitor (96.44% accuracy), while Zhao et al. [114] and Duckworth et al. [113] integrated SHAP to improve transparency in immune and emergency-care predictions. Tasin et al. [115] demonstrated that SHAP provides more stable interpretability than LIME in diabetes forecasting. However, explainable systems remain underutilized in multi-disease and real-time clinical scenarios, limiting physician acceptance and accountability.

#### c) Comparative Analysis and Persistent Gaps

Table 3.2 summarizes key studies in disease-risk prediction, emphasizing their methodology, explainability level, and limitations. Although accuracy rates frequently exceed 95%, interpretability, dataset integration, and inclusion of vulnerable demographics remain unsolved challenges.

### 3.3.2 Survey on Intelligent and Pediatric Healthcare Systems

The integration of AI, IoMT, and mobile health (mHealth) has also transformed pediatric healthcare, promoting continuous and personalized disease management. In pediatric nephrology, such technologies enable early detection, therapy optimization, and longitudinal follow-up for chronic kidney and nephrotic conditions.

Maniam et al. [**?**] developed an IoT–fuzzy-logic framework for chronic kidney disease monitoring, achieving 99% diagnostic accuracy. Wang et al. [**?**] introduced *UrApp*, a mobile system assisting children with nephrotic syndrome in home urine testing, achieving 97% concordance with laboratory analysis. Despite their promise, these systems lacked full clinical integration and real-time clinician alerts.

Table 3.3 provides a comparative overview of recent pediatric monitoring and AI-based nephrology systems, highlighting their key contributions and limitations.

**Telemedicine-Enabled Systems and Predictive Models.** Telemedicine-enabled systems have significantly expanded during the pandemic, particularly in pediatric chronic care. Soler et al. [**?**] observed increased teleconsultation dependence, while Liu and Wang [**?**] demonstrated the effectiveness of IoT-integrated mobile sensing for personalized pediatric feedback. Ye et al. [**?**] and Yang et al. [**?**] further emphasized predictive analytics for steroid

resistance and acute kidney injury, though most systems still operate as opaque black-box models.

**Explainable AI in Pediatric Healthcare Systems.** Explainability has become a key requirement in AI-driven pediatric healthcare systems to ensure clinical trust, safety, and transparency. Filler et al. [**?**] and Talukder et al. [110] stressed that interpretability, fairness, and clinician oversight are prerequisites for adoption. Explainable models capable of revealing variable influence (e.g., biomarkers and demographics) are critical for reliable and accountable clinical decision-making.

Overall, AI-enabled telemonitoring, IoMT frameworks, and predictive modeling have evolved significantly beyond the COVID-19 context. Yet, most current systems remain disease-specific, fragmented, and weakly explainable. Bridging these gaps requires multi-disease, interoperable architectures that unify sensing, analytics, and ethical clinical decision support principles embodied in the proposed AI-LMS, AI-RiskX, and NS-Assist frameworks introduced in the subsequent chapter.

# Conclusion

This chapter provided an integrated overview of intelligent healthcare systems built on AI, IoMT, and MCC. The analysis of pandemic-focused works (Part I) highlighted the essential role of digital intelligence in rapid diagnosis, forecasting, and remote monitoring, while also revealing key limitations such as narrow disease scope, limited interoperability, and insufficient explainability.

More recent research (Part II) has shifted toward multidisease risk prediction, interpretable AI models, and personalized telemonitoring for chronic and pediatric care, marking a transition from reactive crisis response to continuous and proactive healthcare. Despite this progress, challenges related to data heterogeneity, transparency, ethics, and system integration still hinder widespread adoption.

Overall, the literature underscores the need for intelligent, adaptive, and explainable systems that integrate detection, risk assessment, and long-term monitoring within a unified framework. These insights directly motivate the development of the AI-LMS, AI-RiskX, and NS-Assist frameworks presented in the following part of the thesis.

Table 3.2: Summary of Reviewed Studies in Disease Detection and Risk Prediction

| **Authors** | **Disease Scope** | **AI Methodology** | **Explainability Used** | **Vulnerable Groups** | **Limitations** |
|---|---|---|---|---|---|
| El-Sofany et al. [100] | Single (Diabetes) | XGBoost + SMOTE | None | No | No interpretability |
| Guleria et al. [101] | Single (Heart) | SVM + SHAP/LIME | SHAP, LIME | No | Small dataset, no DL component |
| Yilmaz et al. [102] | Single (Heart) | RF, LR, SVM | None | No | No explainability or vulnerable group focus |
| Prathibha et al. [103] | Single (Thyroid) | ResNet (DL) | None | No | Only image-based, single-disease |
| Awal et al. [105] | Single (Asthma) | BOMLA (ML) | None | No | Dataset imbalance, lacks explainability |
| Heris et al. [106] | Single (Asthma) | KNN | None | No | Risk of overfitting, small dataset |
| Talukder et al. [110] | Single (Cardiovascular) | CNN + Ensemble ML with SHAP | SHAP | No | Disease-specific; lacks multimodal and longitudinal validation; evaluated on UCI CVD dataset (Acc $\approx$ 98.5%) |
| Bilal et al. [111] | Single (Cardiovascular) | DNN + LIME/SHAP + Feature-weighted Forecasting | LIME, SHAP | No | High precision (>98%); focused on structured clinical data; lacks external benchmarking |
| Srinivasu et al. [112] | Single (Diabetes) | CNN + BiLSTM | None | No | Image-based, lacks demographic analysis |
| Zhao et al. [114] | Single (Immune disorders) | XGBoost (VDJMiner) | SHAP | No | Limited to immune repertoire data |
| Duckworth et al. [113] | Single (COVID-related risks) | NN + SHAP | SHAP | No | Limited dataset sources |
| Tasin et al. [115] | Single (Diabetes) | XGBoost, SMOTE | LIME, SHAP | No | Small dataset, lacks demographic profiling |
| Bottrighi et al. [107] | Single (COVID-19) | JRIP (rule-based ML) | None | No | Class imbalance, no explainability |
| Quiroz et al. [108] | Single (COVID-19) | kNN, SVM, NN | None | No | Not generalizable |
| Zhang et al. [104] | Single (Thyroid) | Xception CNN | None | No | Limited to ultrasound/CT data |
| Ahmed et al. [109] | Partial (CVDs) | ML + Statistical modeling | None | No | Genomic-only, lacks clinical variables |

Table 3.3: Comparative overview of recent pediatric monitoring and AI-based nephrology systems.

| **Study** | **Focus Area / Technology** | **Target Population** | **Key Findings** | **Limitations / Gaps** |
|---|---|---|---|---|
| Maniam et al. [**?**] | IoT + Fuzzy Logic for CKD monitoring | Adult CKD patients | 99% renal status accuracy. | Lacks EMR integration; no long-term validation. |
| Wang et al. [**?**] | Mobile *UrApp* for home urine testing | Children with INS | 97% lab agreement; improved family engagement. | No clinician interface or auto-alerts. |
| Veltkamp et al. [**?**] | Epidemiological INS analysis during COVID-19 | Pediatric INS cohorts | Stable incidence; delayed diagnosis under lockdown. | No digital framework proposed. |
| Watanabe et al. [**?**] | Post-pandemic pediatric INS trends | Children with INS (Japan) | Detected higher steroid resistance; tele-follow-up feasible. | No AI or telemonitoring component. |
| Ye et al. [**?**] | ML-based SRNS prediction | Children with INS | 94% accuracy on clinical data. | Limited explainability; no IoMT linkage. |
| Zaorska et al. [**?**] | Neural networks for steroid response prediction | Pediatric nephrotic patients | 92% accuracy. | Black-box model; lacks transparency. |
| Yang et al. [**?**] | ML-based AKI risk prediction | Hospitalized children with INS | Validated on multicenter data. | No real-time IoMT integration. |
| Filler et al. [**?**] | Systematic review of AI in pediatric nephrology | Pediatric domain | Highlights ethical and interpretability challenges. | Need for explainable clinician-in-loop systems. |

# Part II: Contributions

# Chapter 4

# AI-LMS: An AI-Based Long-Term Monitoring System for Patients in Pandemics

## 4.1 Introduction

The COVID-19 pandemic exposed critical weaknesses in global healthcare systems, revealing how traditional hospital-centric models fail to ensure continuity of care during large-scale crises. Beyond this specific event, similar limitations persist in managing chronic or remote patients, where episodic in-person consultations cannot provide timely supervision. These shortcomings highlight the need for intelligent, adaptive digital frameworks capable of continuous monitoring, early risk prediction, and data-driven clinical decision support.

The convergence of Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) provides a solid foundation for addressing these challenges. By combining real-time data acquisition, distributed processing, and predictive analytics, these technologies enable scalable, responsive, and personalized healthcare delivery even under resource-limited or emergency conditions.

This chapter presents the AI-LMS (Artificial Intelligence–based Long-Term Monitoring System) [117], a modular and pandemic-agnostic architecture that supports longitudinal patient supervision. It is important to note that AI-LMS is proposed as a conceptual architectural framework rather than an experimental or implementation-based system. Unlike conventional telemonitoring systems, AI-LMS integrates AI-driven analytics, IoMT-based sensing, and MCC-enabled cloud services into a unified, adaptive platform for intelligent

healthcare delivery.

The remainder of this chapter is structured as follows. Section 4.2 presents the conceptual context and design objectives of AI-LMS. Section 4.3 details the dual-phase healthcare workflow encompassing identification and monitoring. Section 4.4 describes the analytical models underpinning the system's intelligence.

## 4.2 Context and Objectives of AI-LMS

Vulnerable populations, including the elderly, chronically ill, and immunocompromised patients, require proactive monitoring systems capable of anticipating health deterioration rather than merely reacting to symptoms, particularly in pandemic contexts such as COVID-19. Addressing these needs requires intelligent, connected, and scalable healthcare solutions that bridge the gap between hospital-based and home-based care.

The AI-LMS system was designed to address this need by establishing an intelligent, distributed framework that supports early risk detection, longitudinal tracking, and clinical decision support. Its architecture integrates three complementary technologies whose synergy enables both real-time analytics and large-scale adaptability:

- *Artificial Intelligence (AI):* enables patient stratification, predictive modeling, and adaptive learning for personalized decision-making;
- *Internet of Medical Things (IoMT):* facilitates real-time acquisition of physiological and contextual data through connected sensors and wearable devices;
- *Mobile Cloud Computing (MCC):* provides scalable computation, storage, and ubiquitous access for distributed healthcare stakeholders.

Collectively, these components create a unified and intelligent healthcare ecosystem that links patients, clinicians, and analytical engines through bidirectional communication. Unlike conventional telehealth frameworks that primarily transmit data, AI-LMS embeds intelligence across all layers from sensing and inference to clinical validation ensuring adaptive, transparent, and continuous care delivery.

### 4.2.1 Global Architecture Overview

The conceptual design of AI-LMS, shown in Figure 4.1, is organized into three functional and interconnected layers that support the end-to-end healthcare workflow: sensing, mobile-aware computation, and clinical decision-making. These correspond to the *monitoring layer*

(IoMT), the *Mobile Cloud Computing (MCC) layer* providing latency-sensitive and mobile-aware processing, and the *identification and decision layer*. Together, these layers form a closed feedback loop connecting patients, analytical services, and healthcare professionals.

At the sensing layer, the Internet of Medical Things (IoMT) enables continuous acquisition of physiological and environmental data through wearable sensors and mobile health applications. These devices measure vital parameters such as heart rate, body temperature, oxygen saturation ($SpO_2$), and activity level, transmitting them to the MCC infrastructure. Local preprocessing (e.g., signal filtering or data compression) reduces latency and optimizes energy consumption. Beyond data collection, this layer enables patients to actively participate in their own care, transforming them into real-time data contributors within a connected healthcare ecosystem.

The Mobile Cloud Computing (MCC) layer serves as the cognitive and computational core of AI-LMS. Acting as middleware between sensing and decision layers, it aggregates heterogeneous data streams, executes analytical models, and generates real-time alerts and predictive insights. Unlike conventional cloud computing, MCC enables mobile-aware and latency-sensitive distributed intelligence by leveraging both edge and cloud resources in proximity to data sources. This hybrid execution model minimizes communication delays, improves responsiveness, and supports real-time processing of IoMT data streams, which is critical for time-sensitive healthcare applications. In addition, MCC ensures elasticity, fault tolerance, and scalability under high data throughput.

At the upper layer, the identification and decision component enables human-centered supervision and clinical reasoning. Healthcare professionals interact with AI-LMS through interactive dashboards that visualize patient trajectories, risk classifications, and system-generated recommendations. This layer operationalizes the *human-in-the-loop* principle, where AI supports clinicians without replacing their expertise. Physicians can validate or refine automated outputs, annotate cases, and provide feedback that contributes to continuous model improvement. This bidirectional interaction enhances transparency, accountability, and clinical reliability.

As illustrated in Figure 4.1, AI-LMS follows a continuous data feedback cycle structured across three main layers. First, the sensing layer collects physiological and contextual data from IoMT devices, wearables, and mobile applications such as heart rate, temperature, and oxygen levels and transmits them to the cloud. Second, within the cloud (MCC) layer, the data are processed and analyzed using AI techniques to generate real-time predictions, detect anomalies, and issue alerts while ensuring scalability and data security. Finally, the decision

layer translates these insights into actionable information presented through intuitive dashboards, supporting clinicians and patients in decision-making. This closed-loop architecture enables continuous learning and dynamic adaptation to evolving patient conditions and environmental contexts.

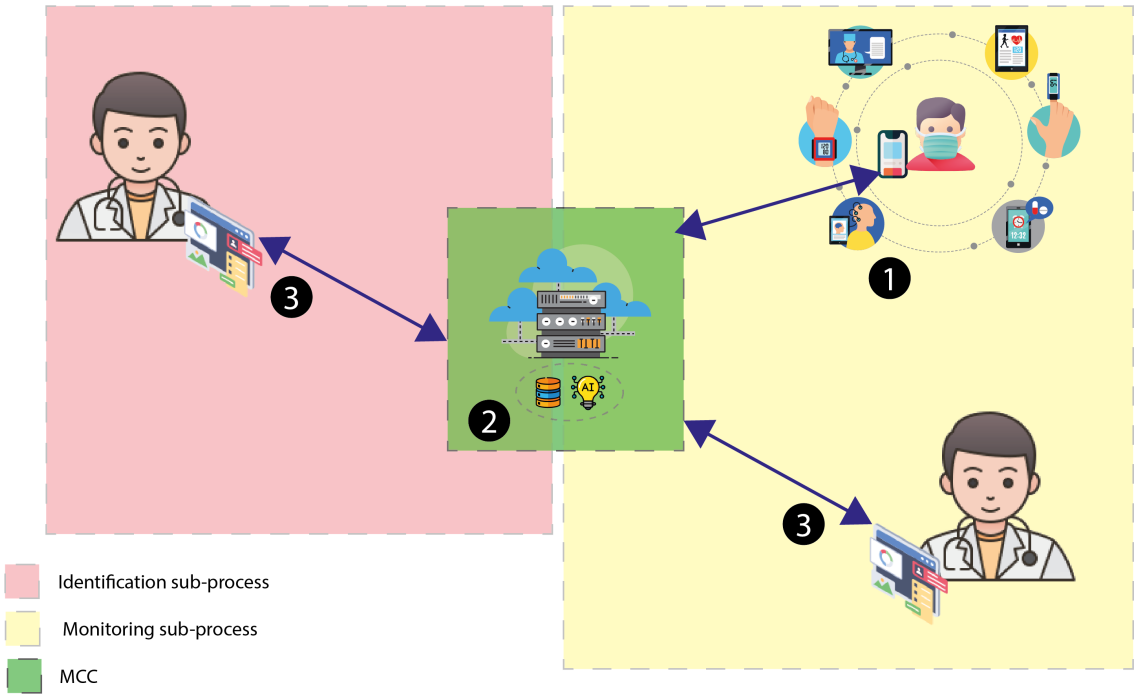



Figure 4.1: Global architecture of the AI-LMS system.

Overall, the AI-LMS architecture balances automation and clinical oversight through its modular and layered design. By integrating IoMT-driven sensing, mobile cloud intelligence, and clinician validation, it establishes a resilient and scalable foundation for telemonitoring in both pandemic and non-pandemic contexts. Its interoperability enables seamless integration with hospital information systems, teleconsultation platforms, and future AI modules, positioning AI-LMS as a flexible and extensible framework for next-generation digital healthcare.

### 4.2.2 Objectives of AI-LMS

Building upon the architectural principles outlined earlier, the development of AI-LMS was guided by three overarching objectives that merge technological innovation with clinical applicability. Each objective transforms a conceptual challenge interoperability, continuity of care, and adaptability into a concrete design requirement for intelligent long-term monitoring.

- **Objective 1: Distributed and Modular Architecture** Design a robust, interop-

erable architecture that integrates AI, IoMT, and MCC to enable real-time patient supervision and intelligent decision support. The framework must manage heterogeneous medical data originating from wearable sensors, remote devices, and structured clinical repositories (EHRs, laboratory results, imaging records). It emphasizes semantic interoperability and ensure data exchange across distributed environments while ensuring compliance with healthcare standards such as HL7 FHIR, GDPR, and HIPAA. This objective establishes the technological foundation for scalability, reliability, and trust across multi-institutional healthcare ecosystems.

- **Objective 2: Dual-phase Healthcare Process** Implement a two-stage process integrating (i) early risk identification and (ii) long-term health monitoring. In the first stage, the system stratifies patients based on clinical, physiological, and demographic indicators to identify those at elevated risk. In the second, it maintains continuous supervision through IoMT-based sensing and adaptive analytics, enabling timely alerts, predictive trend analysis, and personalized care recommendations. This objective operationalizes the full continuum of care anticipation, detection, and follow-up within a unified digital workflow.

- **Objective 3: Validation and Generalizability** Evaluate the performance, adaptability, and usability of AI-LMS under pandemic and chronic-disease scenarios. Validation involves assessing classification accuracy, latency, data throughput, and user experience through simulation and pilot deployments. Adaptability focuses on extending the same architecture to multiple clinical domains such as respiratory, cardiovascular, or metabolic disorders without structural redesign. This ensures that AI-LMS functions as a disease-agnostic and evolvable healthcare framework.

Collectively, these objectives position AI-LMS as a cornerstone for resilient digital health infrastructures. By addressing interoperability, continuity of monitoring, and cross-domain adaptability, the system transcends the limits of traditional telehealth and establishes a scalable paradigm for intelligent, patient-centric care in both routine and emergency contexts.

## 4.3 Healthcare Process: Identification and Monitoring

The AI-LMS workflow is structured around two interdependent sub-processes: *Identification* and *Monitoring*. Together, they form a continuous healthcare cycle that detects at-risk individuals, generates personalized care plans, and supervises patient evolution in real time

through IoMT-based data streams and cloud-hosted AI services. The overall data flow between these phases is shown in Figure 4.2.

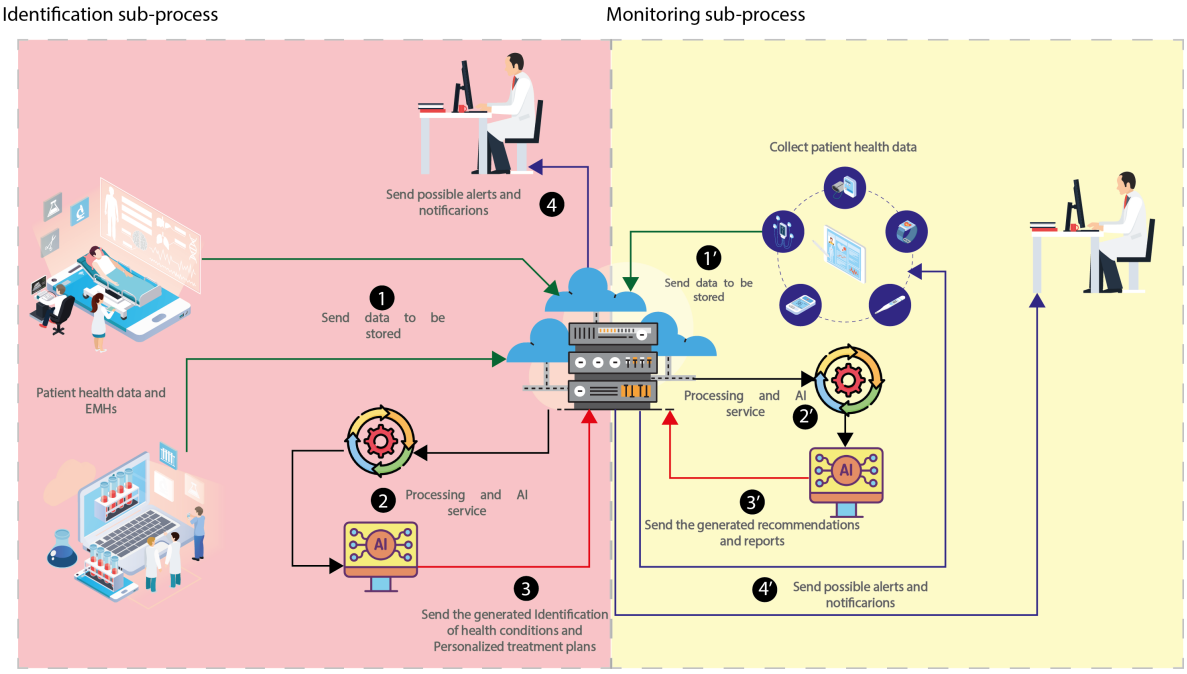



Figure 4.2: Healthcare process flow in AI-LMS: identification and monitoring sub-processes

### 4.3.1 Identification Sub-Process

The identification phase determines whether a patient should be classified as "at risk" of severe complications during a pandemic or other health crisis. It relies on structured clinical data (vital signs, symptoms, laboratory values) and demographic information obtained from Electronic Medical Records (EMRs) [116]. These data are analyzed using AI-based classifiers to produce risk scores and personalized clinical recommendations. The outputs of this phase are twofold:

- (i) a probabilistic risk classification reflecting the patient's vulnerability level, and
- (ii) a corresponding treatment or follow-up plan generated through the decision-support module.

These outputs guide early triage and resource prioritization.

**Process Description:** As illustrated in Figure 4.2 (steps 1 to 4), the identification subprocess enables early detection and triage of patients who may be at risk of clinical deterioration. The process unfolds as follows:

1. **Data acquisition and storage (Step 1):** Patient information is gathered through standard medical consultations or telehealth interactions. All inputs vital signs, laboratory results, imaging summaries, and demographic attributes are transmitted to the MCC infrastructure, where they are stored and formatted for analysis.

2. **Risk classification (Step 2):** Analytical models process these data to estimate each patient's probability of belonging to a high-risk category. Depending on data type, the classifier may employ traditional ML, deep learning, or hybrid AI techniques. This enables early identification of patients who require closer supervision or intervention.

3. **Decision support (Step 3):** For classified high-risk cases, a reasoning model proposes personalized recommendations derived from medical guidelines, patient history, and population-level outcomes. These may include hospitalization advice, treatment adjustment, or telemonitoring enrollment.

4. **Notification (Step 4):** Alerts and recommendations are automatically displayed on the clinician's dashboard. Human review closes the loop, ensuring that final actions are validated by professional judgment before implementation.

The identification logic is formalized in Algorithm 1, which summarizes the data flow from input acquisition to AI-assisted triage and physician validation.

**Algorithm 1** At-Risk Patient Identification Algorithm

**Require:** Patient data and EMRs

**Ensure:** Health-state classification and treatment plan

```
Apply analytical model to assess risk
if patient classified as at-risk then
    Notify healthcare provider
    Generate treatment recommendation
else
    Continue routine observation
end if
Store outcomes in MCC for follow-up
```

This algorithm encapsulates the transition from raw data to clinically interpretable risk evaluation, ensuring that human expertise remains central in the decision cycle.

### 4.3.2 Monitoring Sub-Process

Once a patient has been identified as at-risk, the monitoring phase ensures continuous supervision through IoMT sensors and automated analytics. This process integrates real-time physiological measurements (heart rate, $SpO_2$, temperature, respiration, activity level) with historical Electronic Health Records (EHRs) to provide contextualized, time-aware health tracking.

The monitoring sub-process relies on multiple data sources to ensure continuous and context-aware patient supervision. These inputs consist primarily of IoMT sensor data and Electronic Health Records (EHRs). IoMT data represent real-time physiological measurements collected from wearable or ambient devices, capturing indicators such as heart rate, oxygen saturation, temperature, and activity levels. In parallel, EHRs provide longitudinal clinical information, including the patient's medical history, diagnoses, treatments, and outcomes across multiple care episodes, thereby offering a comprehensive context for ongoing monitoring.

The outputs of this sub-process include several essential components. First, the system generates alerts and notifications whenever abnormal readings or concerning trends are detected, enabling timely medical intervention. Second, it produces predictive analytics and recommendations, which provide AI-driven insights to support proactive clinical decisions. Finally, dashboards and reports are created to visualize patient data trends and summarize key health indicators, facilitating continuous supervision and informed decision-making by healthcare professionals.

**Process Description:** As shown in the yellow region of Figure 4.2 (steps 1' to 4'), the monitoring sub-process ensures continuous supervision of at-risk patients using real-time data streams from IoMT devices. Each step performs a distinct role, progressing from data acquisition to actionable alerts:

1. **Sensor data acquisition (Step 1'):** IoMT devices continuously transmit physiological data to the MCC platform via communication channels.

2. **Model inference (Step 2'):** Incoming data are processed in real time using predictive or rule-based models to detect anomalies or early warning signals. This step focuses on

immediate assessment of the patient's current condition.

3. **Trend analytics (Step 3'):** Beyond instant detection, the system analyzes temporal patterns by aggregating historical and incoming data to identify trends, variations, and deviations from baseline behavior. This enables a longitudinal understanding of patient health evolution.

4. **Alert generation (Step 4'):** When predefined thresholds or abnormal trends are detected, automated alerts are generated and sent to both patients and clinicians, along with contextual recommendations for timely intervention.

This process transforms continuous sensor streams into actionable intelligence, supporting preventive interventions and reducing diagnostic latency.

The logic governing continuous monitoring is summarized in Algorithm 2. It illustrates the event-driven nature of the process, where IoMT inputs dynamically trigger analysis, alerting, and reporting.

**Algorithm 2** Continuous Monitoring Algorithm

**Require:** Real-time IoMT streams and EHRs

**Ensure:** Alerts, analytics, and visualization reports

```
while monitoring active do
    Acquire and preprocess data
    Evaluate health indicators
    if risk exceeds threshold then
        Issue alert and recommendation
    else
        Continue observation
    end if
end while
```

The algorithm demonstrates how AI-LMS sustains closed-loop supervision detecting anomalies, providing feedback, and enabling early medical intervention before clinical deterioration occurs.

The identification and monitoring sub-processes together create a seamless pipeline from risk prediction to continuous oversight. Their operation depends on a coordinated set of analytical models, which are detailed in the next section.

## 4.4 Analytical Models in AI-LMS

The cognitive intelligence of AI-LMS relies on a set of interoperable analytical models that operate synergistically across the system's workflow. Each model fulfills a distinct analytical role classification, reasoning, and predictive monitoring while remaining modular and adaptable to various healthcare contexts. Together, they form the decision-making backbone that transforms heterogeneous data into actionable clinical knowledge (Figure 4.3).

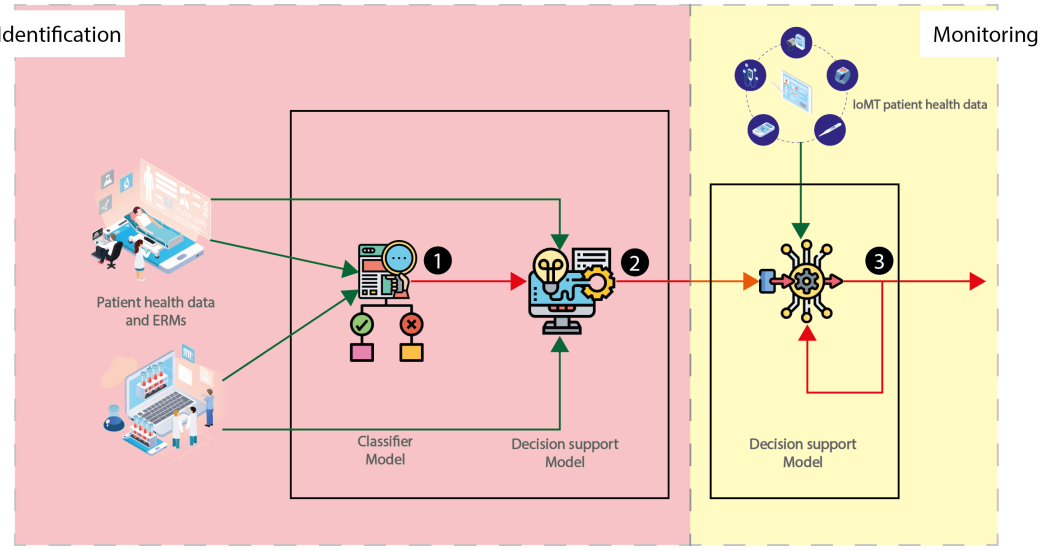



Figure 4.3: Analytical models in AI-LMS: core components for patient classification, decision support, and predictive monitoring.

1. *Risk Classification Model (Phase 1).* Following classification, this model translates analytical outputs into clinically interpretable recommendations. It fuses data-driven inference with knowledge-based reasoning, aligning predictive results with established medical protocols and expert rules. By analyzing patient history, comorbidities, medication profiles, and temporal evolution, it recommends targeted actions such as therapeutic adjustments, hospitalization prioritization, or teleconsultation scheduling. The model incorporates human feedback into its knowledge base, enabling progressive refinement through expert validation. While the AI-LMS framework keeps this module disease-agnostic, it provides the conceptual foundation for domain-specific extensions.

2. *Risk Identification and Decision Model (Phase 2).* This model interprets classification outcomes to generate actionable recommendations. It integrates rule-based reasoning and data-driven inference to align algorithmic predictions with clinical logic. By analyzing patient history, comorbidities, and treatment outcomes, it suggests optimized

care pathways such as hospitalization, medication adjustments, or follow-up scheduling. The model remains disease-agnostic and adaptable.

3. *Monitoring and Predictive Analytics Model (Phase 3).* This model governs the real-time monitoring phase, analyzing continuous data streams from IoMT devices to detect anomalies, forecast deterioration, and guide preventive intervention. It integrates adaptive learning mechanisms that refine predictive thresholds based on individual baselines and historical evolution. Depending on the scenario, the model may employ data-driven analytics, knowledge-based inference, or hybrid configurations that combine both. It produces alerts, visual trends, and predictive scores that support proactive clinical actions while minimizing false alarms. This dynamic feedback system transforms continuous sensing into predictive intelligence, ensuring early response and reducing diagnostic latency.

Collectively, these three models establish the cognitive layer of AI-LMS. Their modularity ensures scalability, interpretability, and cross-domain applicability allowing seamless integration of specialized subsystems such as **AI-RiskX** for explainable risk prediction and **NS-Assist** for rule-based clinical reasoning. By combining data analytics, expert knowledge, and continuous feedback, AI-LMS achieves an adaptive equilibrium between automation and human oversight a key attribute for trustworthy, long-term digital healthcare systems.

## 4.5 Conclusion

The AI-LMS framework demonstrates the potential of converging Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) to overcome the structural and logistical limitations of traditional healthcare delivery. By fusing real-time sensing, distributed analytics, and adaptive decision support, AI-LMS provides a resilient foundation for intelligent, patient-centered telemonitoring capable of sustaining care continuity even under pandemic or resource-limited conditions. It is important to emphasize that AI-LMS is presented as a conceptual architectural framework, and its contributions focus on system design rather than experimental validation or implementation.

The main contributions of this chapter are threefold. First, it proposed a distributed, modular architecture that ensures interoperability and communication among IoMT devices, cloud services, and clinical interfaces. Second, it established a dual-phase healthcare workflow that unites early risk identification with continuous patient monitoring, supported by AI-driven analytics. Third, it introduced a multi-model cognitive layer comprising classification,

reasoning, and predictive components that transforms heterogeneous data into interpretable and actionable clinical knowledge. Collectively, these contributions advance the design of adaptive, scalable, and explainable digital-health ecosystems.

Building upon the architectural and methodological foundations established in this chapter, the following section introduces AI-RiskX, the dedicated risk-assessment module of AI-LMS. It extends the principles of intelligent monitoring toward explainable, multi-disease risk prediction, providing deeper insight into model transparency and clinical interpretability.

# Chapter 5

# AI-RiskX: An Explainable Deep Learning approach for Identifying At-Risk patients during Pandemics

## 5.1 Introduction

Building on the foundations established by the AI-LMS framework, this chapter introduces AI-RiskX [118] the intelligent risk-identification core of the proposed system. While AI-LMS addressed long-term monitoring and continuous supervision, AI-RiskX focuses specifically on the early detection of patients at risk of severe complications during pandemic or emergency conditions.

Early and accurate risk identification is essential to enable timely intervention, optimize healthcare resources, and reduce mortality. However, as extensively reviewed in Chapter 3, existing AI-based healthcare models often remain limited in scope, focusing on single diseases, lacking transparency in decision-making, and showing weak adaptation to diverse demographic profiles [100, 102, 106]. These gaps underscore the need for a multidisease, explainable, and demographically aware system capable of supporting fair and clinically interpretable predictions.

AI-RiskX responds to these limitations through an explainable deep learning approach that integrates structured clinical and demographic data for risk classification. Unlike conventional black-box models, it combines predictive accuracy with interpretability by leveraging SHapley Additive exPlanations (SHAP) [66] and post-hoc demographic reasoning. This dual perspective enables clinicians to understand not only *what* the system predicts but also *why*.

The following sections detail the motivations behind AI-RiskX, its architectural design, data integration and modeling pipeline, demographic-aware stratification logic, and explainability layer. Together, these components define a transparent, inclusive, and deployable risk prediction framework. The empirical evaluation of AI-RiskX including performance metrics and interpretability analyses is presented in the next chapter.

## 5.2 Motivations and Key Contributions

The development of AI-RiskX was motivated by persistent limitations in current AI-based risk classification systems, particularly their narrow clinical focus, lack of demographic adaptation, and opacity in decision-making. To be effective in pandemic and multidisease contexts, AI systems must move beyond isolated disease prediction and evolve toward interpretable, inclusive, and deployment-ready solutions.

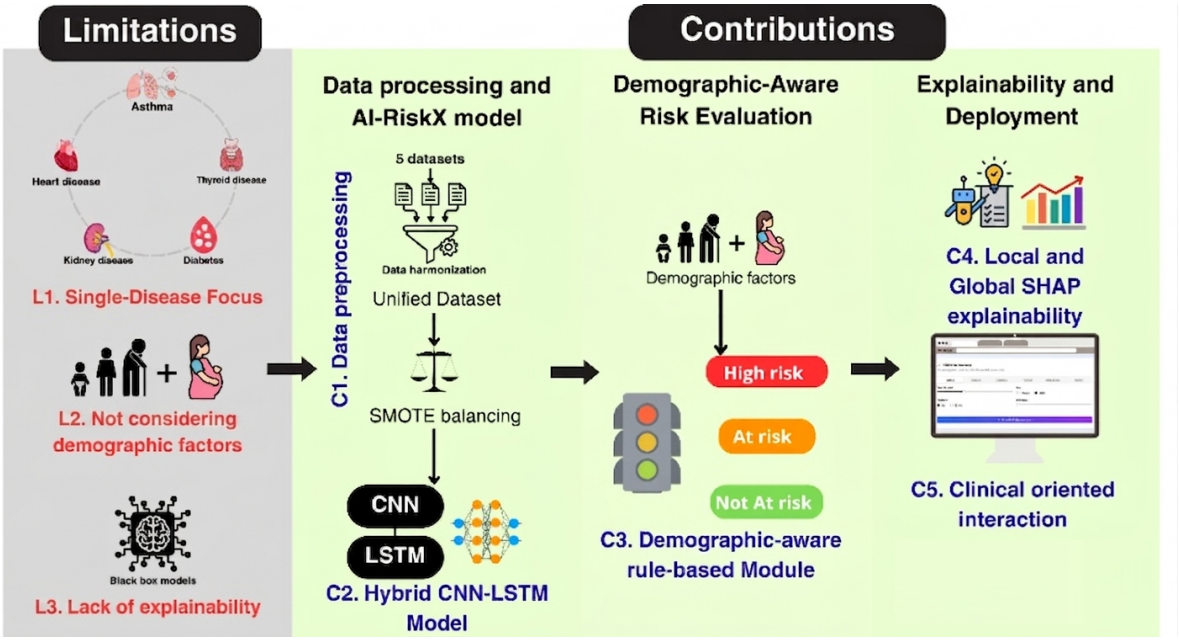



Figure 5.1: Overview of AI-RiskX: an explainable and demographic-aware risk-classification pipeline.

### 5.2.1 Challenges in Existing Systems

Despite rapid progress in clinical machine learning, most existing approaches still exhibit structural and ethical weaknesses that limit their reliability in practice. The main challenges motivating the design of AI-RiskX are as follows:

- **Single-Disease Limitation:** Conventional models are typically trained for one pathology, such as diabetes or heart disease, preventing generalization to patients with multiple comorbidities a common reality during pandemics [101, 103].
- **Lack of Demographic Sensitivity:** Many algorithms ignore contextual factors such as age, pregnancy, or pediatric status, producing biased outcomes that compromise fairness and safety for vulnerable subgroups [101, 105].
- **Opaque Decision Logic:** Black-box models often fail to explain how predictions are derived, hindering clinician trust, accountability, and regulatory approval for clinical use [103, 105].

### 5.2.2 Core Contributions of AI-RiskX

AI-RiskX addresses these limitations through an integrated, multidimensional pipeline that combines advanced data processing, hybrid deep learning, and post-hoc interpretability. Its main contributions are summarized below:

- **Unified Multidisease Dataset:** Integration and harmonization of five heterogeneous clinical datasets were achieved through a structured pipeline involving schema alignment, feature standardization, unified label mapping, and missing-value handling. The datasets were merged via row-wise concatenation into a unified feature space of 79 attributes, where non-shared features were completed using zero-value imputation. This approach ensures structural and semantic consistency, enabling the model to learn generalizable patterns across diseases rather than dataset-specific correlations.
- **Hybrid CNN–LSTM Risk Model:** A deep hybrid architecture capturing both spatial and temporal dependencies within structured health data, allowing improved generalization across heterogeneous clinical features.
- **Demographic-Aware Rule-Based Refinement:** A fairness-oriented layer that adjusts raw model outputs using interpretable demographic logic (age, pregnancy, pediatric status), yielding ethically grounded risk categories.
- **SHAP-Based Explainability:** Integration of SHapley Additive exPlanations (SHAP) [66] to provide both global and local interpretability, allowing clinicians to visualize the most influential features driving each prediction.

- **Clinician Interface and Deployment Readiness:** A lightweight, modular interface supporting clinical review and integration with healthcare systems via standardized APIs, ensuring practical usability and scalability.

Together, these contributions position AI-RiskX as a transparent, multidisease, and ethically aware decision-support module within the broader AI-LMS ecosystem. The next section details its architectural workflow and operational phases.

## 5.3 System Architecture and Workflow

The AI-RiskX system is built around a modular, multi-phase architecture that ensures flexibility, transparency, and accuracy in risk stratification. Each phase of the workflow from raw data integration to explainable outputs plays a distinct role in transforming heterogeneous patient data into actionable clinical insights. Figure 5.2 presents an overview of the four key phases that comprise the AI-RiskX pipeline.

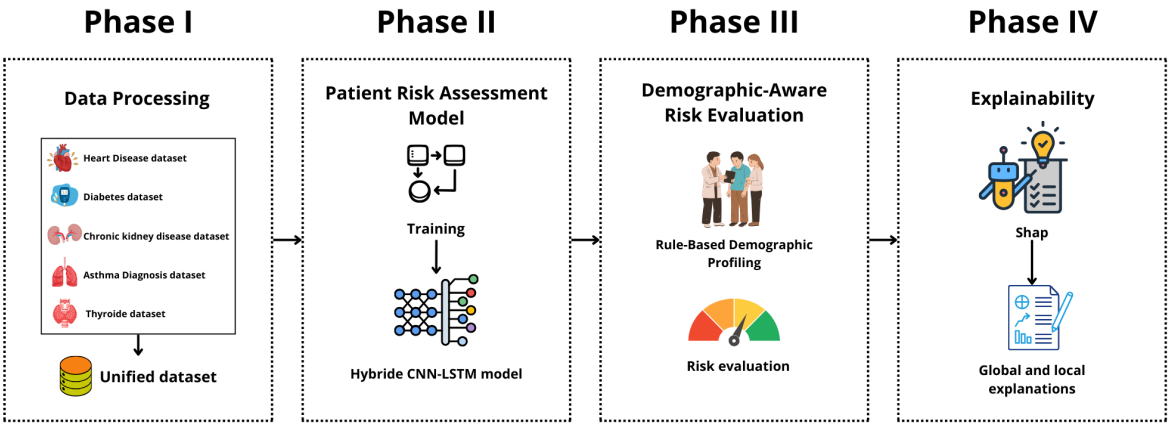



Figure 5.2: AI-RiskX multi-phase architecture for risk classification and interpretation.

### Phase I – Data Processing

In the early stage, data from different sources covering chronic diseases like diabetes, heart disease, asthma, kidney issues, and thyroid disorders are brought together and standardized into one combined dataset. This unified construction improves generalizability beyond single-disease models. Standard preprocessing steps including normalization of features, handling

of missing values, and class-imbalance mitigation through SMOTE (Synthetic Minority Oversampling Technique) are applied to ensure a balanced training set suitable for deep learning.

## Phase II – Patient Risk Assessment Model

The system's foundation is a hybrid CNN–LSTM model built to capture both spatial and temporal features within patient data. The convolutional layers capture inter-feature relationships (for example between test results and clinical observations), while the LSTM layers model sequential dependencies that may indicate evolving risk over time. This design enables robust classification of patients across multiple disease classes and supports accurate risk prediction using structured health data.

## Phase III – Demographic-Aware Risk Evaluation

To incorporate fairness and contextual sensitivity, a rule-based module refines the raw model outputs by integrating demographic information such as age, pregnancy status, and pediatric classification. Based on this demographic profiling, each patient is stratified into one of three risk categories: *High risk*, *At risk*, or *Not at risk*. This phase addresses limitations of traditional AI models that overlook demographic factors and ensures more targeted risk assessment and intervention planning.

## Phase IV – Explainability

Recognizing the need for transparency in clinical AI, this phase integrates SHapley Additive exPlanations (SHAP) to generate both global (population-level) and local (individual-level) feature attributions. In practice, local explanations are computed by applying Deep SHAP to individual predictions, producing feature contribution scores for each patient instance. Global explanations are then obtained by aggregating these SHAP values across all samples, typically using the mean absolute contribution of each feature to derive an overall importance ranking.

Clinicians can inspect which features most influenced each risk prediction and understand the model's reasoning. The system presents these explanations through an interface designed for clinical review, enhancing trust, interpretability, and adoption in real-world settings.

Together, these four phases form a cohesive pipeline that converts raw clinical data into explainable risk classifications. While the broader AI-LMS system described earlier addressed

long-term continuous monitoring of patients, AI-RiskX enhances its early-stage decision support module by specifically targeting the identification and classification of individuals at risk.

## 5.4 Experimental Framework and Methodological Design

This section presents the complete design and implementation of the AI-RiskX system. It includes the unified data foundation, the architecture of the proposed model, post-classification demographic-aware stratification, and integration of explainability for clinical transparency. These components form a robust pipeline for identifying vulnerable patients during pandemics.

### 5.4.1 Data Processing

In contrast to other works, which often concentrated on a single disease, this study integrates five heterogeneous medical datasets to design and validate the AI-RiskX framework. Together, these datasets encompass a range of chronic conditions namely heart disease, diabetes, thyroid disorders (hypo- and hyperthyroidism), asthma, and chronic kidney disease (CKD) forming a broad and representative basis for multidisease risk modeling. Each dataset combines demographic information with key clinical measurements, supporting a comprehensive evaluation of patient vulnerability.

For this investigation, all patient records are interpreted within the context of a pandemic scenario (e.g., COVID-19). Under this assumption, the model assesses individual vulnerability levels by analyzing pre-existing health conditions that may worsen infectious-disease outcomes.

Specifically, the UCI Heart Disease dataset [137] provides structured cardiovascular profiles widely used for binary classification between healthy and at-risk patients. The Healthcare Diabetes dataset [138] includes 768 samples characterized by conventional clinical indicators and binary outcome labels identifying diabetic status. For thyroid dysfunction detection, the Hypo/Hyperthyroidism dataset [141] integrates both numerical and categorical features, enabling accurate discrimination among normal, hypo-, and hyper-thyroid conditions. The Asthma Diagnosis dataset [139] comprises anonymized, heterogeneous attributes suitable for supervised asthma-detection modeling. Finally, the UCI Chronic Kidney Disease (CKD)

dataset [140] contains 400 labeled instances distinguishing individuals with CKD from healthy counterparts.

Together, these heterogeneous datasets provide a multidimensional foundation for multidisease risk modeling. To enable unified learning, all datasets were harmonized into a common feature space and subsequently merged using a row-wise concatenation strategy, where each source contributes its samples mapped onto the same set of 79 standardized features. Features not originally present in a given dataset were completed using zero-value imputation, representing the absence of specific clinical measurements. This integration process ensures structural and semantic consistency across all records, resulting in a unified, balanced, and clinically interpretable dataset that serves as the backbone of the AI-RiskX system and supports the learning of generalizable patterns across diseases.

### 5.4.2 Data Integration and Harmonization

To enable consistent multidisease modeling, a comprehensive normalization and harmonization process was applied across five heterogeneous clinical datasets, encompassing heart disease, diabetes, asthma, thyroid disorders, and chronic kidney disease. This procedure established structural, semantic, and statistical consistency within the unified multidisease dataset, ensuring that the integrated data maintained reliability across all sources.

The harmonization workflow comprised several sequential steps:

- **Column Cleaning:** Non-essential administrative variables such as PatientID, DoctorInCharge, and EducationLevel were removed to prevent data leakage and preserve patient anonymity.
- **Schema Alignment:** Variable names and encodings were standardized (for example, Gender was normalized to sex) to unify schema conventions across datasets.
- **Structural Validation:** Each dataset was verified to contain an identical set of 79 harmonized features, with consistent data types (numeric, binary, or categorical) across all records.
- **Label Mapping:** Disease categories were encoded under a unified labeling framework: healthy (0), asthma (1), diabetes (2), heart disease (3), kidney disease (4), and thyroid disorder (5).

- **Handling Missing Features:** Missing values were addressed using proxy-based matching or statistical imputation mean substitution for numerical fields and mode imputation for categorical ones ensuring data completeness across all 79 attributes.

This harmonization pipeline ensured that all datasets were structurally aligned, semantically coherent, and statistically compatible, forming a robust foundation for subsequent multidisease training and inference within the AI-RiskX framework.

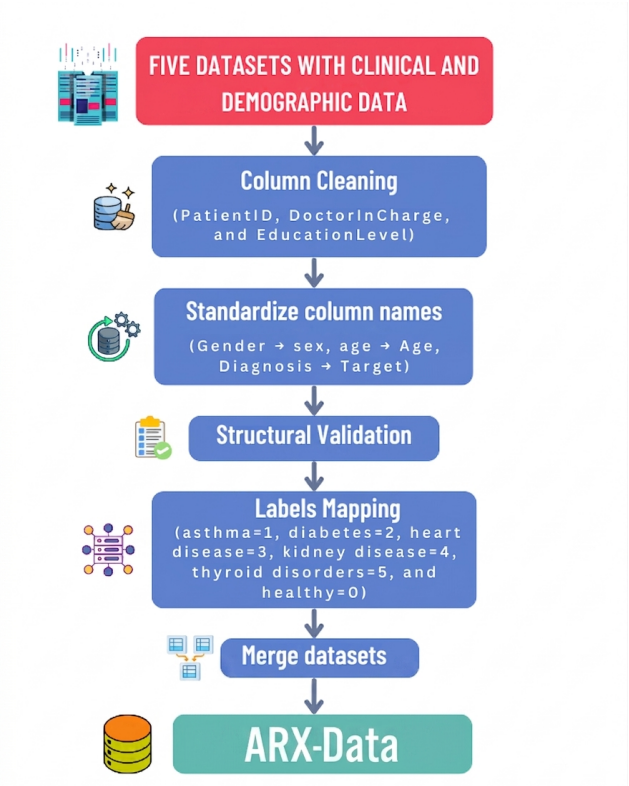



Figure 5.3: ARX-Data creation and harmonization workflow.

The final dataset comprises 26,125 samples, each with 79 harmonized features, reshaped to a $(79, 1)$ format suitable for CNN-based feature extraction. Dataset statistics are shown in Tables 5.1 and 5.2.

Table 5.1: Overview of the integrated ARX-Data.

| **Property** | **Description** |
|---|---|
| **Total Samples** | 26,125 |
| **Number of Features** | 79 |
| **Feature Categories** | Demographic, Lifestyle, Clinical, Thyroid, Cardiac, and Respiratory attributes. |
| **Target Variable** | Multilabel disease representing five disease categories. |
| **Source Integration** | Combined from five publicly available medical datasets. |

Table 5.2: Feature group overview.

| **Group** | **Count** | **Examples** |
|---|---|---|
| **Demographic** | 5 | Age, Sex, Ethnicity. |
| **Lifestyle** | 6 | Smoking habits, Physical activity level. |
| **Cardiac** | 12 | Resting blood pressure (Trestbps), Cholesterol (Chol), Maximum heart rate (Thalach). |
| **Diabetes** | 6 | Glucose, Insulin, Body Mass Index (BMI). |
| **Kidney** | 11 | Blood urea (Bu), Serum creatinine (Sc), Sodium (Sod). |
| **Thyroid** | 22 | Thyroid-stimulating hormone (TSH), Total thyroxine (TT4), Triiodothyronine (T3). |
| **Asthma** | 17 | Wheezing, Coughing, Shortness of breath. |

### Class Balancing and Normalization

Due to significant class imbalance (e.g., asthma = 124 samples), the Synthetic Minority Oversampling Technique (SMOTE) was applied exclusively to the training set to prevent data leakage and ensure unbiased evaluation. SMOTE generates synthetic samples for minority classes by interpolating between a data point and its nearest neighbors, according to:

$$x_{\text{new}} = x + \lambda \cdot (x_{\text{nn}} - x), \quad \lambda \in [0, 1] \tag{5.1}$$

where the Euclidean distance used to identify nearest neighbors is defined as:

$$d(x_i, x_j) = \sqrt{\sum_{m=1}^{M} (x_{i,m} - x_{j,m})^2} \tag{5.2}$$

In practice, SMOTE was implemented using the `fit_resample` function, which automatically generates synthetic samples for minority classes until a balanced class distribution is achieved. As illustrated in Figure 5.4, this process transforms an imbalanced dataset into a balanced one by increasing the representation of underrepresented classes through synthetic data generation.

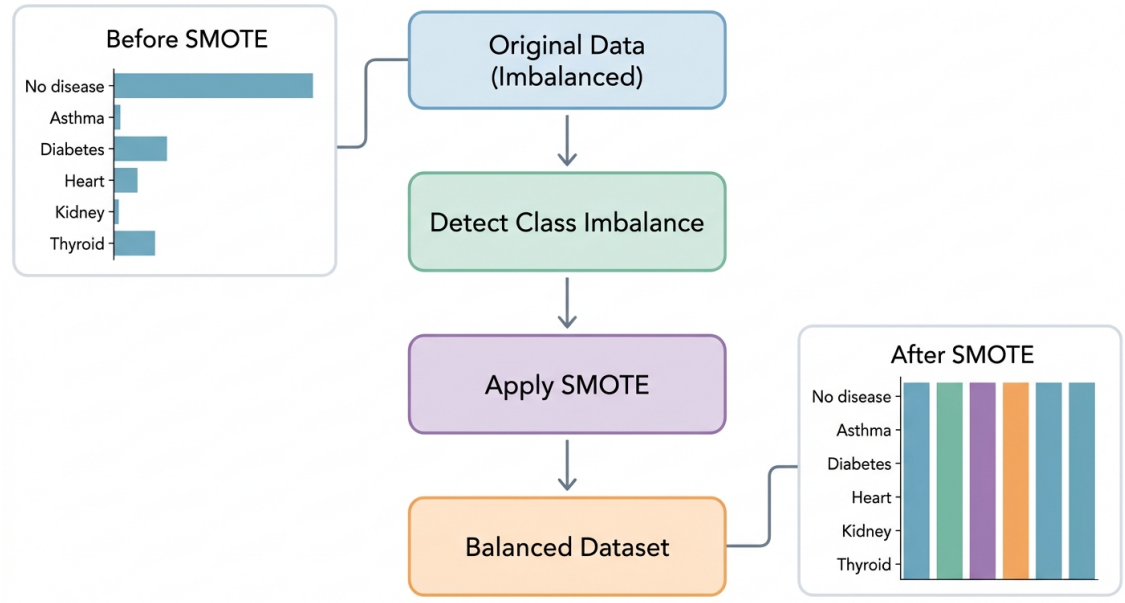



Figure 5.4: SMOTE-based data augmentation process.

This approach increases the representation of underrepresented classes while preserving the underlying data structure. As shown in Table 5.3, all classes were balanced to 22,420 samples. However, this resulted in a high proportion of synthetic data for minority classes, reaching 99.45% for asthma and exceeding 95% for most underrepresented diseases, while the majority class (no disease) required no augmentation.

Although this balancing strategy improves model learning and reduces class bias, the high percentage of synthetic samples necessitates careful validation. To address this, the model was evaluated using separate validation and test sets, ensuring that performance reflects true generalization rather than overfitting to augmented data.

Table 5.3: Distribution of samples across disease categories before and after SMOTE balancing.

| **Label** | **Disease** | **Samples (Before)** | **After SMOTE** | **Augmented (%)** |
|---|---|---|---|---|
| 0 | No disease | 22,420 | 22,420 | 0.00% |
| 1 | Asthma | 124 | 22,420 | 99.45% |
| 2 | Diabetes | 952 | 22,420 | 95.75% |
| 3 | Heart | 526 | 22,420 | 97.65% |
| 4 | Kidney | 250 | 22,420 | 98.88% |
| 5 | Thyroid | 1,853 | 22,420 | 91.74% |
| **Total** | | **26,125** | **134,520** | – |

**Normalization and Partitioning**

To prepare for model training, all numeric features were normalized using Min–Max scaling:

$$x_N = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5.3}$$

This approach enhances both training stability and the speed of convergence. The complete dataset was randomly shuffled and subsequently partitioned into three subsets: 70% for training, 20% for validation, and 10% for testing.

This harmonization strategy resolves cross-dataset heterogeneity by enforcing a shared feature space and unified semantics. By aligning all datasets into a consistent representation, the model can learn generalizable patterns across diseases rather than relying on dataset-specific correlations.

### 5.4.3 Patient Risk Assessment Model

To achieve reliable multidisease classification, AI-RiskX was designed as a progressive modeling framework that evolved from traditional machine learning baselines to a fully integrated deep learning architecture. Initially, several classical machine learning (ML) models were implemented to establish performance references on the structured clinical dataset. Three widely adopted algorithms—Logistic Regression, Random Forest, and XGBoost—were

trained and evaluated under identical experimental settings. Logistic Regression, employing standardized input features and L2 regularization (`C = 1.0`) optimized with the `lbfgs` solver, provided an interpretable yet limited benchmark for nonlinear relationships. The Random Forest ensemble, comprising 200 trees (`n_estimators = 200`), achieved stable results using Gini impurity and class balancing but showed difficulty generalizing across highly imbalanced disease categories. Similarly, XGBoost (`learning_rate = 0.1`, `max_depth = 6`, `n_estimators = 200`) with early stopping and subsampling (`subsample = 0.8`) offered improved performance yet remained constrained in representing complex temporal and spatial dependencies within the 79 clinical features. Overall, while these ML baselines established a necessary benchmark, their predictive capacity plateaued due to limited representational depth, motivating the transition toward deep learning models capable of capturing richer feature interactions.

Building on these findings, the deep learning phase introduced several neural architectures that substantially enhanced performance. A 1D Convolutional Neural Network (CNN) was first implemented to extract localized spatial patterns from the structured inputs, employing two convolutional layers (64 filters, kernel size = 3) followed by batch normalization, max pooling, and dense layers (64 and 32 neurons). Despite its efficiency in feature abstraction, it lacked temporal awareness, which led to the development of Recurrent Neural Network (RNN) models. The LSTM and BiLSTM variants incorporated temporal dependencies through stacked recurrent layers (64–128 units) with dropout and L2 regularization, improving generalization and sequence learning across longitudinal health data. Finally, the hybrid CNN–LSTM architecture integrated both spatial and sequential learning streams, achieving the best multidisease classification accuracy within AI-RiskX. Complementary experiments with a Transformer-based (LLM–BERT) configuration where tabular data were reformatted into textual representations (e.g., "Age: 45; Gender: Male; ...") demonstrated that the hybrid CNN–LSTM remained superior for structured healthcare data. These results confirmed that deep learning approaches, particularly hybrid sequential–spatial models, significantly outperformed classical ML baselines by effectively modeling the complex interdependencies among heterogeneous clinical attributes.

### Hybrid CNN–LSTM Design

The AI-RiskX hybrid CNN–LSTM architecture was conceived to jointly exploit local feature extraction and long-term temporal dependencies within multidimensional clinical data. The network integrates three parallel one-dimensional convolutional branches (1D-CNNs) and

a dedicated LSTM pathway, enabling simultaneous spatial and sequential learning. Each CNN branch employs a distinct kernel size of 3, 5, and 7 to capture heterogeneous local temporal patterns. Within each branch, two consecutive Conv1D layers (64 filters each) with ReLU activation are followed by batch normalization to stabilize training and a max-pooling layer (pool size = 2) to reduce dimensionality and extract dominant features. In parallel, the LSTM stream consists of a stacked configuration of two recurrent layers containing 64 and 32 units, respectively, each followed by batch normalization to improve convergence and mitigate vanishing gradients.

The outputs of the three convolutional streams and the LSTM branch are then concatenated and flattened, forming a unified latent representation that captures both spatial abstractions and temporal continuity. This combined feature vector is propagated through two fully connected layers (64 and 32 neurons with ReLU activation) and a dropout layer (rate = 0.3) to minimize overfitting. Finally, a softmax output layer produces the predicted probabilities across the six disease classes. Overall, this multi-branch hybrid design enables AI-RiskX to achieve high discriminative power by learning hierarchical spatial patterns while preserving clinically meaningful temporal dynamics.

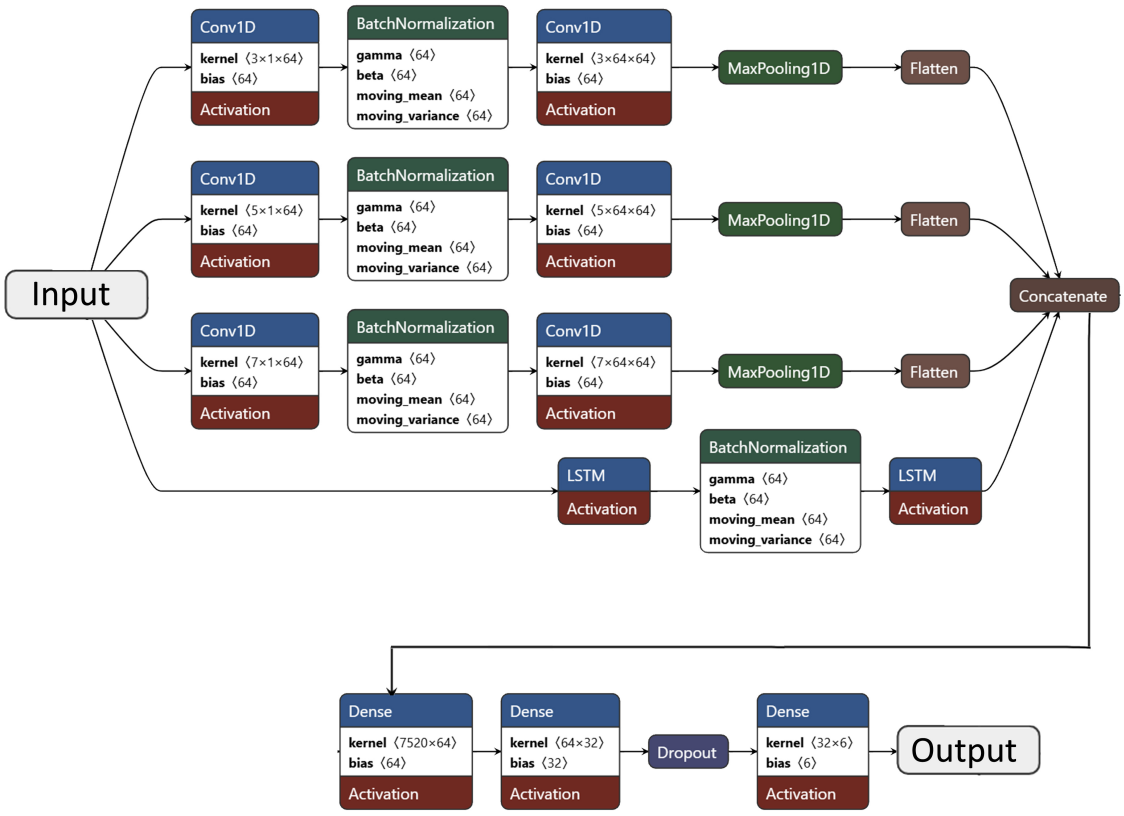



Figure 5.5: Proposed AI-RiskX hybrid CNN–LSTM model architecture.

Table 5.4: Layer-wise structure of the CNN–LSTM architecture.

| Stage | Layer(s) | Output Shape |
|---|---|---|
| **Input** | 79 numeric clinical features. | (79, 1) |
| **Feature Extraction** | Three Conv1D layers (64 filters, kernel sizes = 3, 5, and 7) with ReLU activation and batch normalization. | (79, 64) each |
| **Feature Enrichment** | Second Conv1D block (same configuration as above). | (79, 64) each |
| **Pooling** | MaxPooling1D (pool size = 2) applied to each convolutional branch. | (39, 64) each |
| **LSTM Branch** | LSTM(64) + Batch Normalization → LSTM(32). | (32) |
| **Fusion** | Flatten and concatenate all convolutional and LSTM branches. | – |
| **Dense Layers** | Dense(64, ReLU) → Dense(32, ReLU) + Dropout(0.3). | (32) |
| **Output Layer** | Dense(6, Softmax). | (6) |

### Training and Optimization

The AI-RiskX hybrid CNN–LSTM model was trained using categorical cross-entropy as the objective loss function and optimized via the Adam optimizer, chosen for its adaptive learning capability and stable convergence on heterogeneous clinical data. To promote robust generalization, a stratified 5-fold cross-validation procedure was employed, ensuring that class distributions remained balanced across all folds. Each model was trained with a batch size of 32, a learning rate of 0.001, and up to 30 epochs, with early stopping applied to mitigate overfitting and preserve optimal weights.

To further address the issue of class imbalance, the SMOTE was utilized exclusively on the training data, leaving the validation and test sets unaltered to prevent data leakage and maintain fair evaluation integrity. This preprocessing step ensured adequate representation of minority disease classes during learning while preserving realistic assessment conditions.

Empirical results demonstrated that the CNN–LSTM hybrid architecture consistently outperformed all baseline models, including traditional methods (Logistic Regression, Random Forest, and XGBoost) as well as standalone deep learning models such as CNN-only,

LSTM-only, and Transformer-based BERT architectures. These outcomes underscore the model's superior ability to capture complex spatial-temporal dependencies and multidimensional clinical patterns across multiple chronic disease categories, validating the robustness and adaptability of the AI-RiskX framework.

### 5.4.4 Demographic-Aware Risk Evaluation

To ensure clinically meaningful and ethically balanced predictions, the AI-RiskX system incorporates a rule-based demographic module that refines the model's diagnostic output by embedding patient-specific contextual information. This module operates downstream of the disease classification stage and integrates demographic attributes to stratify individuals into three intuitive risk levels: High Risk, At Risk, and Not at Risk.

The evaluation begins by identifying key demographic indicators that influence vulnerability, including age group classified as children (under 18 years), adults (18–59 years), and elderly (60 years and older) alongside pregnancy status, represented by a binary flag. These demographic factors are analyzed jointly with the disease prediction results to derive a refined final label. Patients simultaneously exhibiting a chronic condition and belonging to a vulnerable demographic group (children, elderly, or pregnant women) are categorized as High Risk, reflecting their heightened susceptibility to complications. Conversely, patients with a disease diagnosis but without demographic vulnerability are labeled At Risk, while individuals who are both clinically healthy and demographically stable are classified as Not at Risk.

The decision mechanism governing this logic is formalized in Algorithm 3, which illustrates how demographic context is systematically integrated into the final output. This rule-based refinement enhances the interpretability, fairness, and ethical alignment of AI-RiskX, ensuring that predictive outcomes support more equitable and patient-centered clinical interventions.

**Algorithm 3** Patient Risk Stratification

**Require:** Patient data *data*, trained model *model*

**Ensure:** Patient risk category

1: Obtain *age_group* and *pregnancy_status* from *data*

2: Predict patient *status* using *model* and select the class with the highest probability

3: Define demographic vulnerability:

$$vulnerable \leftarrow (age\_group \in \{\text{child, elderly}\}) \vee (pregnancy\_status = \text{pregnant})$$

4: **if** *status* $\neq$ Healthy **and** *vulnerable* **then**

5: **Assign:** *High Risk*

6: *Disease detected in a vulnerable patient.*

7: **else if** *status* $\neq$ Healthy **or** *vulnerable* **then**

8: **Assign:** *At Risk*

9: *Disease is detected, or the patient is clinically vulnerable despite being currently healthy.*

10: **else**

11: **Assign:** *Not at Risk*

12: *Patient is healthy and does not belong to a vulnerable demographic group.*

13: **end if**

### 5.4.5 Explainability with SHAP

To enhance transparency and support clinical decision-making, the AI-RiskX system integrates Explainable Artificial Intelligence (XAI) techniques, enabling healthcare professionals to interpret and validate the model's predictions. Building upon the theoretical foundations of SHAP presented in the previous chapter, this work focuses on its practical integration within the proposed system.

SHAP is employed to quantify the relative contribution of each input feature to a given prediction, allowing clinicians to understand how specific attributes influence the model's output. In the context of AI-RiskX, this facilitates the interpretation of key clinical variables and their role in risk assessment, thereby improving trust and usability in real-world settings.

Due to the computational complexity of exact Shapley value estimation, the system adopts the Deep SHAP approximation, which is specifically designed for deep learning architectures. This approach is applied to the fused CNN–LSTM representation just before the final classification layer, ensuring that both spatial and temporal patterns learned by the model are

reflected in the explanation process.

The system provides two complementary levels of interpretability. Global explanations highlight the most influential features across the entire dataset, offering insight into overall model behavior. In contrast, local explanations focus on individual predictions, decomposing each output into feature-level contributions that explain the rationale behind a specific decision.

By integrating SHAP-based explanations within the user interface, AI-RiskX transforms complex model outputs into interpretable visual insights. This integration bridges the gap between algorithmic predictions and clinical reasoning, enabling physicians to validate results using domain knowledge and supporting informed, transparent, and accountable decision-making in healthcare environments.

## 5.5 Conclusion

This chapter introduced the design and methodology of the AI-RiskX system an explainable, deep learning–based approach for identifying at-risk patients during pandemics. Grounded in the limitations of existing AI healthcare models, AI-RiskX integrates a multidisease dataset, a hybrid CNN–LSTM architecture, demographic-aware risk stratification, and SHAP-based interpretability into a unified and deployable framework.

The system addresses critical needs for fairness, transparency, and robustness in clinical decision support, offering both technical innovation and practical utility. From its balanced data foundation to its interpretable outputs, AI-RiskX is positioned as a comprehensive solution for early risk identification in pandemic contexts.

In the next chapter, we present a detailed evaluation of the system, including performance metrics, ablation studies, and interpretability analyses, to empirically validate its effectiveness and readiness for clinical deployment.

# Chapter 6

# Evaluation and Results of the AI-RiskX System

## 6.1 Introduction

Building upon the methodological and architectural design presented in the previous chapter, this section provides an in-depth empirical evaluation of the **AI-RiskX** system. The objective is to validate its predictive accuracy, robustness, interpretability, and suitability for real-world clinical integration within telemonitoring infrastructures.

A comprehensive set of experiments was performed to assess the system's generalization and adaptability under multidisease conditions. These include comparative analyses against classical and deep learning baselines, ablation studies to isolate architectural contributions, cross-validation for statistical robustness, and interpretability assessment using SHAP (SHapley Additive exPlanations). Metrics such as accuracy, precision, recall, F1-score, and AUC are employed to ensure multi-faceted evaluation.

Furthermore, a user-oriented implementation of AI-RiskX is showcased through a web interface that enables real-time inference, demographic-aware risk stratification, and explainable visualization. Together, these experiments and demonstrations provide solid evidence of AI-RiskX's reliability and clinical viability. Ultimately, this evaluation not only validates algorithmic performance but also demonstrates the feasibility of AI-RiskX as a foundational component of resilient, AI-driven telemonitoring systems during pandemic and post-pandemic healthcare scenarios.

## 6.2 Comparative Performance Evaluation

To establish a reference benchmark, three conventional algorithms Logistic Regression, Random Forest, and XGBoost were trained on two data configurations: the combined dataset and its balanced counterpart. As summarized in Table 6.1, Logistic Regression achieved an accuracy of 89.95% on the full dataset but declined to 70.68% when tested on the balanced version, underscoring its susceptibility to class imbalance.

Conversely, Random Forest and XGBoost demonstrated consistently strong results across both scenarios, attaining 96.77% and 96.99% on the combined dataset, and 96.84% and 96.98% on the balanced dataset, respectively. These findings indicate that although tree-based ensemble methods can mitigate certain imbalance effects, their representational power remains limited for modeling complex, multi-disease interactions inherent in healthcare datasets.

To further evaluate the contribution of deep learning architectures, multiple networks were explored, including CNN, LSTM, BiLSTM, and LLM-BERT. When tested on individual disease datasets, BiLSTM achieved superior performance for heart disease, diabetes, HHT, and CKD, while LSTM yielded the best accuracy for Alzheimer's disease (AD). This consistency highlights the capacity of LSTM-based networks to effectively capture temporal dependencies in sequential clinical data.

When extended to the integrated ARX-Data (Unified AI-RiskX dataset), deep learning models clearly outperformed their classical counterparts. The proposed hybrid CNN–LSTM model obtained the highest accuracy of 98.78% on the balanced dataset exceeding CNN (98.67%), LSTM (96.97%), BiLSTM (96.13%), and LLM-BERT (86.02%). Even on the imbalanced dataset, the hybrid model maintained a leading accuracy of 94.55%, demonstrating its robustness. These outcomes underscore the CNN–LSTM architecture's ability to jointly encode spatial and temporal features, thereby producing richer, disease-agnostic representations suitable for unified medical risk assessment.

The CNN–LSTM hybrid clearly outperforms both classical and other deep learning models, especially under multidisease, imbalanced data conditions. Its superior generalization, high accuracy, and robust learning capacity confirm its suitability for clinical deployment in high-stakes environments such as pandemic healthcare response.

Table 6.1: Performance comparison of classical and deep learning models for multidisease prediction under different dataset configurations.

| **Approach** | **Dataset** | **Model** | **Acc.** | **Prec.** | **Rec.** | **F1** |
|---|---|---|---|---|---|---|
| **Standalone** | Heart | LSTM | 96.56 | 96.56 | 96.55 | 96.55 |
| | Diabetes | LSTM | 96.93 | 96.93 | 96.92 | 96.92 |
| | HHT | LSTM | 96.34 | 96.34 | 96.33 | 96.33 |
| | AD | LSTM | 95.20 | 95.20 | 95.19 | 95.19 |
| | CKD | LSTM | 96.25 | 96.25 | 96.24 | 96.24 |
| | Heart | BiLSTM | 97.07 | 97.07 | 97.05 | 97.05 |
| | Diabetes | BiLSTM | 97.40 | 97.40 | 97.39 | 97.39 |
| | HHT | BiLSTM | 96.57 | 96.57 | 96.55 | 96.55 |
| | AD | BiLSTM | 94.78 | 94.77 | 94.75 | 94.75 |
| | CKD | BiLSTM | 97.50 | 97.50 | 97.49 | 97.49 |
| | Heart | CNN | 89.75 | 89.75 | 89.70 | 89.72 |
| | Diabetes | CNN | 86.82 | 86.82 | 86.81 | 86.81 |
| | HHT | CNN | 91.21 | 91.21 | 91.20 | 91.20 |
| | AD | CNN | 93.32 | 93.32 | 93.32 | 93.32 |
| | CKD | CNN | 76.25 | 76.25 | 76.23 | 76.23 |
| **Combined** | ARX-Data | Log. Reg. | 89.95 | 88.64 | 89.95 | 87.75 |
| | ARX-Data | Rand. For. | 96.77 | 96.34 | 96.77 | 96.55 |
| | ARX-Data | XGBoost | 96.99 | 96.62 | 96.99 | 96.80 |
| | ARX-Data | LLM-BERT | 79.35 | 79.30 | 79.21 | 79.26 |
| | ARX-Data | LSTM | 93.16 | 93.16 | 93.12 | 93.13 |
| | ARX-Data | BiLSTM | 90.91 | 90.91 | 90.89 | 90.89 |
| | ARX-Data | CNN | 94.26 | 94.26 | 94.24 | 94.24 |
| | ARX-Data | **CNN–LSTM** | **94.55** | **94.55** | **94.53** | **94.53** |
| **Combined–Balanced** | ARX-Data | Log. Reg. | 70.68 | 89.40 | 70.68 | 76.21 |
| | ARX-Data | Rand. For. | 96.84 | 96.47 | 96.84 | 96.65 |
| | ARX-Data | XGBoost | 96.98 | 96.68 | 96.98 | 96.81 |
| | ARX-Data | LLM-BERT | 86.02 | 86.01 | 85.95 | 85.97 |
| | ARX-Data | LSTM | 96.97 | 96.97 | 96.95 | 96.95 |
| | ARX-Data | BiLSTM | 96.13 | 96.13 | 96.12 | 96.12 |
| | ARX-Data | CNN | 98.67 | 98.67 | 98.66 | 98.66 |
| | ARX-Data | **CNN–LSTM** | **98.78** | **98.79** | **98.77** | **98.77** |

## 6.3 Comparison with Existing Literature

The performance of the proposed AI-RiskX model is further evaluated in comparison with representative studies reviewed in Chapter 3. As highlighted in the literature review, most existing AI-based healthcare models focus on single-disease prediction tasks, achieving high accuracy but lacking generalization across multiple conditions, explainability, and demographic awareness.

For example, El-Sofany et al. [100] proposed an XGBoost-based model for diabetes prediction, achieving an accuracy of 97.4%, while Yilmaz et al. [102] employed classical machine learning techniques for heart disease detection with accuracies ranging between 92% and 97%. Similarly, Prathibha et al. [103] applied deep learning (ResNet) for thyroid disorder classification, and Awal et al. [105] developed an asthma prediction model using BOMLA. Despite their promising results, these approaches remain limited to single-disease scenarios and do not support unified risk prediction across multiple conditions.

More recent works, such as Talukder et al. [110] and Bilal et al. [111], introduced explainability techniques including SHAP and LIME, achieving high accuracy levels above 98%. However, these models are still restricted to specific diseases and do not incorporate demographic-aware analysis or multidisease integration.

In contrast, the proposed AI-RiskX system provides a unified multidisease prediction framework while maintaining competitive and often superior performance. The hybrid CNN–LSTM model achieves an accuracy of up to 98.78% and AUC values ranging from 0.982 to 0.999, demonstrating strong discriminative capability across all disease classes. Additionally, AI-RiskX integrates SHAP-based explainability, enabling transparent interpretation of predictions, and incorporates demographic-aware risk stratification, enhancing its clinical applicability and fairness.

Table 6.2 summarizes the comparison between AI-RiskX and selected studies from the literature.

Table 6.2: Comparison of AI-RiskX with representative studies from the literature.

| Study | Scope | Method | Accuracy | Explainability | Demographic |
|---|---|---|---|---|---|
| El-Sofany et al. [96] | Single | XGBoost + SMOTE | 97.4% | No | No |
| Yilmaz et al. [98] | Single | RF, SVM, LR | 92–97% | No | No |
| Prathibha et al. [99] | Single | ResNet (DL) | 95–97% | No | No |
| Awal et al. [100] | Single | BOMLA (ML) | 90–95% | No | No |
| Talukder et al. [102] | Single | CNN + Ensemble + SHAP | 98.5% | Yes (SHAP) | No |
| Bilal et al. [103] | Single | DNN + SHAP/LIME | >98% | Yes (SHAP, LIME) | No |
| **AI-RiskX (Proposed)** | **Multi** | **CNN–LSTM Hybrid** | **98.78%** | **Yes (SHAP)** | **Yes** |

From this comparison, it is evident that although existing models achieve high predictive performance, they remain limited in scope and applicability. AI-RiskX distinguishes itself by combining high accuracy with multidisease capability, explainability, and demographic awareness within a single unified framework. These characteristics make it more suitable for real-world clinical deployment, particularly in complex healthcare scenarios involving comorbidities and heterogeneous patient populations.

## 6.4 Ablation Study on Model Components

To evaluate the specific role and contribution of each sub-module within the proposed AI-RiskX architecture, a detailed ablation study was conducted. The dataset was partitioned into three disjoint subsets: 70% for training, 20% for validation, and 10% for testing. SMOTE was applied exclusively to the training set to address class imbalance, while the validation and test sets were kept unchanged to preserve the original data distribution. The validation set was used for model tuning and early stopping, whereas the test set was used only for final performance evaluation. This experimental setup ensures an unbiased assessment and allows the isolated analysis of each component's contribution under consistent conditions.

Three model variants were analyzed:

- **LSTM-only model:** focuses solely on capturing temporal relationships among sequential patient records, without integrating any spatial extraction mechanism.
- **CNN-only model:** concentrates on learning spatial representations from clinical feature maps, disregarding sequential dependencies.
- **CNN–LSTM hybrid (AI-RiskX):** fuses both temporal and spatial modeling streams into a single unified deep architecture.

The comparative outcomes of these configurations are reported in Table 6.3. The CNN-only network achieved an accuracy of 98.67%, highlighting its effectiveness in learning localized feature interactions within structured clinical data. The LSTM-only model reached 96.97%, confirming its strength in modeling temporal sequences but revealing limitations in representing spatial dependencies.

In contrast, the integrated CNN–LSTM design achieved superior performance with 98.78% accuracy, 98.79% precision, 98.77% recall, and an F1-score of 98.77%. These improvements illustrate how convolutional and recurrent layers complement each other, where CNN layers extract hierarchical spatial cues and LSTM layers encode longitudinal dependencies across patient timelines.

The ablation analysis thus demonstrates that the joint inclusion of convolutional and recurrent modules is essential for accurately modeling multifactorial disease patterns, enabling more robust and generalizable multidisease risk predictions.

Table 6.3: Ablation study results comparing different architectural configurations on the balanced ARX-Data.

| **Model** | **Acc. (%)** | **Prec. (%)** | **Rec. (%)** | **F1 (%)** |
|---|---|---|---|---|
| LSTM only | 96.97 | 96.97 | 96.95 | 96.95 |
| CNN only | 98.67 | 98.67 | 98.66 | 98.66 |
| **CNN–LSTM(AI-RiskX)** | **98.78** | **98.79** | **98.77** | **98.77** |

## 6.5 Cross-Validation and Statistical Robustness Analysis

To ensure a reliable and unbiased evaluation of the proposed model, a 5-fold cross-validation strategy was adopted. In this setting, the dataset is partitioned into five equally sized subsets, where, at each iteration, four folds are used for training and the remaining fold for testing. This process is repeated five times, allowing each subset to serve once as a validation set. The final performance metrics are computed as the average across all folds, providing a robust estimation of the model's generalization capability. The choice of five folds represents a trade-off between computational efficiency and statistical reliability, and is widely adopted in machine learning for datasets of moderate size.

The summary presented in Table 6.4 indicates that the hybrid CNN–LSTM model achieved consistently strong results across all performance indicators. The system attained an average accuracy of 98.72% and an AUC of 99.52%, both accompanied by low standard deviations, confirming that the model remains robust and stable under multiple resampling scenarios.

Table 6.4: Statistical summary of cross-validation results obtained using the CNN–LSTM hybrid model (Mean ± Standard Deviation).

| **Metric** | **Mean ± Std (%)** |
|---|---|
| Accuracy | 98.72 ± 0.11 |
| Precision | 98.71 ± 0.10 |
| Recall | 98.73 ± 0.09 |
| F1-Score | 98.71 ± 0.08 |
| AUC | 99.52 ± 0.03 |

These observations reinforce the statistical reliability of AI-RiskX, highlighting minimal performance variation across folds.

To further substantiate these findings, multiple inferential tests commonly adopted in machine-learning research were conducted. Confidence intervals (95%) were calculated for each metric $M$ according to:

$$CI_{95\%} = \bar{M} \pm t_{\alpha/2,k-1} \times \frac{s}{\sqrt{k}} \tag{6.1}$$

where $\bar{M}$ denotes the mean value, $s$ the standard deviation, and $k$ the number of folds (here, $k = 5$). For instance, for accuracy ($\bar{M} = 98.72$, $s = 0.11$), the resulting 95% confidence interval is $[98.58, 98.86]$, confirming the model's narrow variance band.

To examine whether performance improvements over baseline methods were statistically meaningful, paired $t$-tests were carried out between the CNN–LSTM model and each comparator. The corresponding test statistic was defined as:

$$t = \frac{\bar{d}}{s_d/\sqrt{k}} \tag{6.2}$$

This analysis confirmed that the CNN–LSTM hybrid significantly outperformed both classical and standalone deep-learning baselines, validating its statistical robustness across repeated experimental runs.

## 6.6 ROC Curve Analysis

To thoroughly evaluate the classification performance of the AI-RiskX model across multiple disease categories, a Receiver Operating Characteristic (ROC) analysis was conducted. This evaluation illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across varying decision thresholds, providing insight into the model's sensitivity and specificity.

The Area Under the Curve (AUC) is used as the primary performance metric, reflecting the model's ability to distinguish between classes. As shown in Figure 6.1, the ROC curves for all classes are concentrated near the upper-left corner of the plot, indicating strong discriminative capability.

The AUC values range from 0.982 to 0.999 across the different classes, demonstrating consistently high classification performance. Although slight variations are observed between classes, all curves remain close to the ideal boundary, confirming the model's robustness and reliability in distinguishing between disease categories.

Overall, these results highlight the effectiveness of the CNN–LSTM-based AI-RiskX model in multi-class classification tasks, supporting its applicability in clinical decision-support scenarios where accurate and consistent predictions are essential.

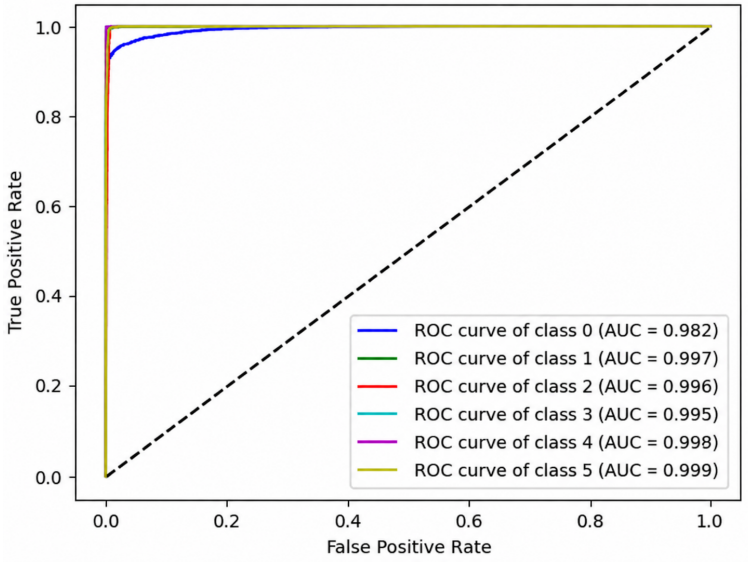



Figure 6.1: ROC curves of the CNN–LSTM model for multi-class disease classification. The curves illustrate high discriminative performance, with AUC values ranging from 0.982 to 0.999 across all classes.

## 6.7 Confusion Matrix Evaluation

To examine and verify the classification behavior of the AI-RiskX framework, confusion matrices were produced for both the validation and testing phases. These matrices offer a granular perspective on the model's per-class predictive accuracy and provide insight into the distribution of misclassifications, allowing a more precise assessment of category-level performance and model limitations.

**Validation Phase Analysis:** As presented in Figure 6.2a, the confusion matrix derived from the validation set reveals high predictive consistency across all disease categories, as shown by the dominant diagonal alignment. Most samples were accurately classified, with only minor deviations observed. Specifically, 3% of healthy samples were incorrectly labeled as thyroid disease, 1% of diabetes instances were categorized as healthy, and 1% of thyroid cases were similarly assigned to the healthy class. These few errors likely stem from shared clinical manifestations and overlapping feature profiles a common occurrence among diseases with intersecting symptom patterns.

**Testing Phase Analysis:** During the testing stage (Figure 6.2b), comparable trends were confirmed, demonstrating strong model generalization. The CNN–LSTM classifier maintained accuracy levels between 96% and 100%, with very limited misclassification rates. Notably, 4% of healthy records were incorrectly predicted (distributed as 1% diabetes and 3% thyroid), whereas 1% of diabetic and 1% of thyroid samples were misidentified as healthy. This level of performance reflects the system's robust generalization and diagnostic reliability across heterogeneous medical data.

The near-perfect results observed in the confusion matrix can be explained by the strong discriminative power of the selected clinical features and the use of SMOTE-based data balancing. Additionally, consistent performance across 5-fold cross-validation confirms that the model generalizes well and that these results are not due to overfitting or data leakage.

The confusion matrix evaluation confirms that AI-RiskX consistently achieves accurate multidisease classification while maintaining minimal false negatives a critical factor for early risk detection and effective clinical intervention. Such stability across both validation and test datasets highlights the model's dependability for large-scale screening and its potential integration into real-world health monitoring systems.

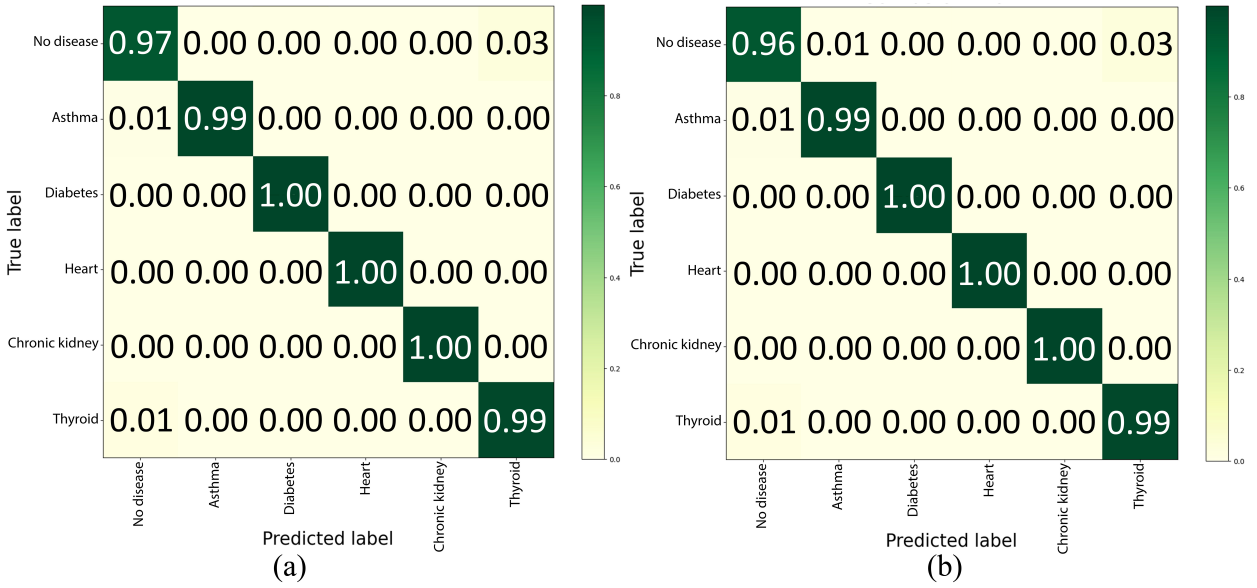



Figure 6.2: Confusion matrix of the CNN–LSTM model on the ARX-Data: (**a**) validation set and (**b**) testing set.

## 6.8 Explainability Through SHAP Interpretations

Ensuring interpretability is essential for deploying AI systems in clinical practice, particularly when algorithmic outputs guide medical decisions. To enhance transparency, the AI-RiskX framework integrates SHAP (SHapley Additive exPlanations), a well-established technique for explaining machine learning predictions. SHAP assigns each input feature a quantitative contribution score toward a specific prediction, allowing medical professionals to explore the reasoning behind model outputs at both global (dataset-wide) and local (instance-level) scales.

After training the CNN–LSTM network, SHAP analysis was conducted on the merged representation of the convolutional and recurrent layers, just before the final dense stage. This joint representation enables an integrated examination of how spatial and temporal patterns collectively shape disease risk predictions.

### 6.8.1 Configuration-Specific Explanations

Two configurations of SHAP analysis were performed to capture feature relevance across different model structures:

- Individual disease models: Each AI-RiskX variant was trained and evaluated on a

single disease dataset independently. SHAP was applied afterward to identify the most influential features specific to that condition.

- Unified multidisease model: SHAP was also applied to the combined AI-RiskX model trained on the full integrated dataset. This ensured that significant diagnostic indicators remained interpretable even after multi-condition fusion.

### 6.8.2 Global and Local Interpretations

The SHAP framework produced two complementary layers of interpretability:

- Global analysis summarized how each variable influenced predictions across the full dataset, highlighting the most impactful clinical indicators overall.
- Local analysis focused on individual patient cases, showing how specific feature values contributed to each prediction and enabling case-level transparency.

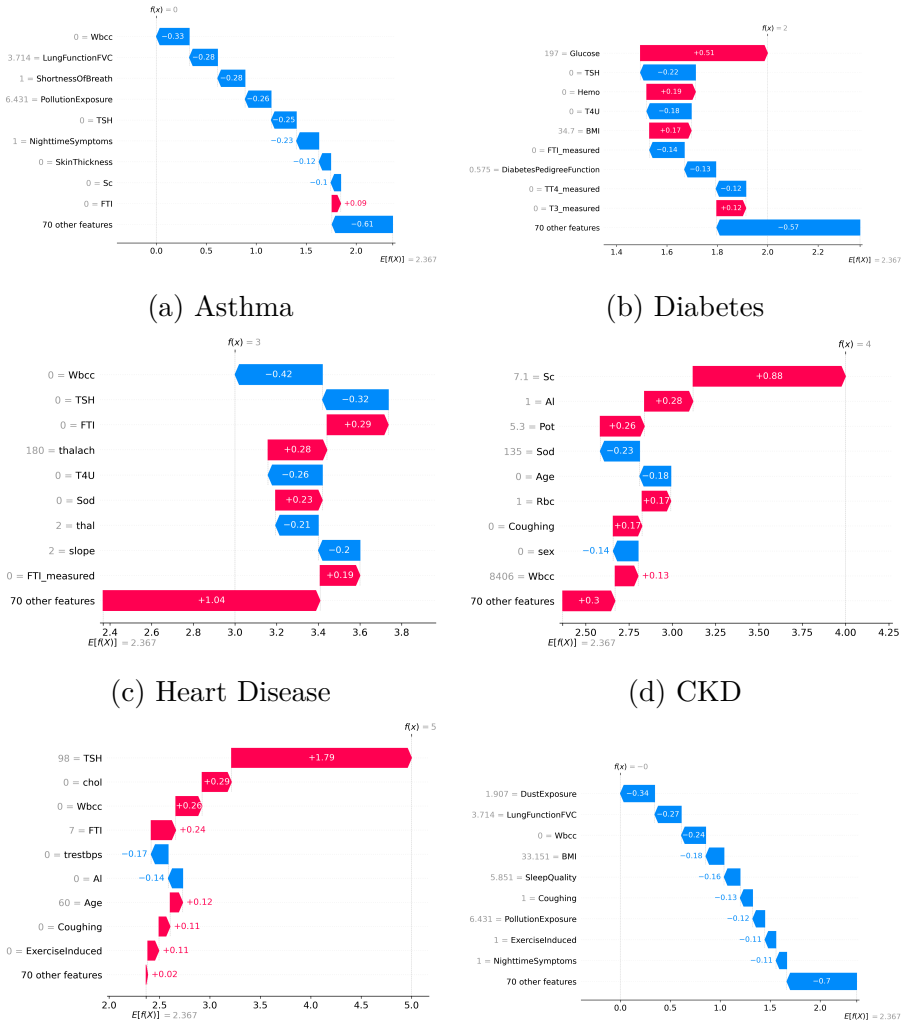
### 6.8.3 Key Insights Across Disease Categories

Across the different disease categories, the SHAP analysis revealed feature importance patterns that were fully consistent with clinical reasoning. For asthma, respiratory variables such as white blood cell count and forced vital capacity (FVC) were the most influential determinants of prediction (Figures/chapter6/ 6.3a, 6.4a). In the case of diabetes, metabolic indicators including glucose concentration, body mass index (BMI), and the diabetes pedigree function were dominant contributors (Figures/chapter6/ 6.3b, 6.4b). For heart disease, the model relied primarily on cardiovascular parameters such as maximum heart rate, chest pain type, and slope (Figures/chapter6/ 6.3c, 6.4c). In chronic kidney disease, biochemical measures particularly serum creatinine and potassium levels emerged as the most critical factors (Figures/chapter6/ 6.3d, 6.4d). Finally, for thyroid disorders, hormonal markers such as TSH and T4U consistently exhibited high contribution scores, reflecting their established diagnostic relevance (Figures/chapter6/ 6.3e, 6.4e).

In the unified AI-RiskX configuration, these indicators maintained their prominence (Figures/chapter6/ 6.3f, 6.4f). Features including TSH, BMI, white blood cell count, and dust exposure retained strong predictive significance across multiple diseases, demonstrating the model's capacity to generalize meaningful biomarkers in an interpretable manner.

### 6.8.4 Clinical Relevance and Interpretability

The comparative SHAP analysis validates that AI-RiskX not only delivers high accuracy but also maintains explainability across diverse diseases. Importantly, the integration of datasets did not dilute key feature relationships; rather, it reinforced them. By embedding SHAP into the model pipeline, AI-RiskX empowers clinicians with clear justifications for each prediction thereby supporting ethical, transparent, and accountable decision-making in high-risk healthcare scenarios.

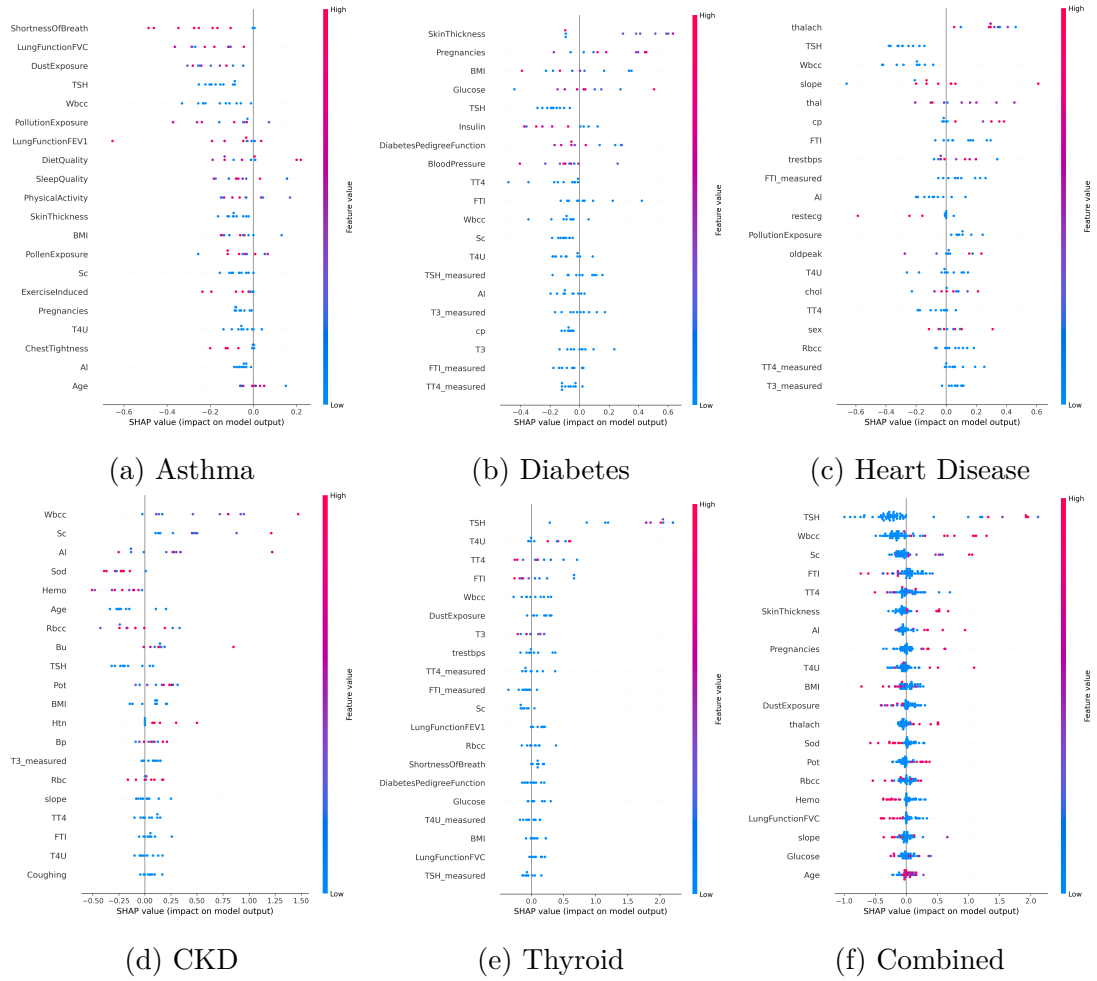



(a) Asthma (b) Diabetes

(c) Heart Disease (d) CKD

(e) Thyroid (f) Combined

Figure 6.3: SHAP waterfall plots showing local feature contributions for disease classification. Red indicates increased risk contribution; blue denotes a decrease.




(a) Asthma (b) Diabetes (c) Heart Disease

(d) CKD (e) Thyroid (f) Combined

Figure 6.4: Global SHAP feature importance for CNN–LSTM across disease categories. Feature rankings reflect average contribution to predictions.

## 6.9 System Implementation and Interactive Interface

To ensure practical deployment and clinical accessibility, the AI-RiskX framework was implemented as a web-based application built using the Gradio library [122]. This environment allows clinicians to enter patient data, obtain real-time diagnostic predictions, and review interpretable explanations associated with each model output. Through this dynamic interface, the system facilitates transparency, reproducibility, and informed medical decision-making in daily practice.

In contrast to conventional opaque deep learning models, AI-RiskX combines explainable neural computation with clinically validated rule-based reasoning. This integration strengthens professional confidence, promotes the adoption of AI-driven support systems, and aligns

predictive analysis with established healthcare procedures.

The application is structured around three core modules: (i) data entry, (ii) risk prediction and stratification, and (iii) explainability. Each module contributes to a coherent diagnostic workflow, ensuring a smooth and logical user experience from data input to interpretive visualization.

### 6.9.1 Structured Data Entry

The data entry module provides a user-friendly interface through which healthcare professionals can record both general and disease-specific patient information. Standardized fields are included for demographic parameters such as age (adjustable via sliders), sex (radio buttons), pregnancy status, and ethnicity. Additional panels are dedicated to each clinical category cardiac, diabetic, renal, respiratory, and thyroid incorporating specialized inputs like blood pressure, glucose concentration, and hormone levels.

This modular structure ensures accurate and consistent data collection, while maintaining accessibility for users with varying levels of technical expertise. A visual example of the data entry interface is provided in Figure 6.5, illustrating the clarity and organization of the input workflow.

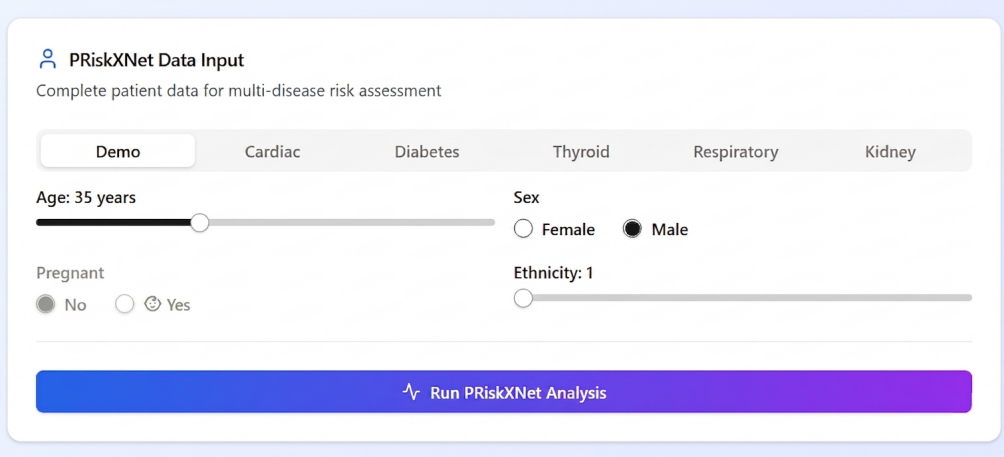



Figure 6.5: Interactive data entry form for demographic and clinical parameters.

### 6.9.2 Disease Prediction and Risk Stratification

When the user submits the completed form, the system forwards the input data to the CNN–LSTM network, which classifies the patient into one of six diagnostic categories: asthma, diabetes, thyroid disorder, chronic kidney disease, heart disease, or no disease.

In parallel, a rule-based stratification module evaluates relevant demographic and clinical attributes to generate a personalized risk category: high risk, at risk, or not at risk. For instance, an older adult (aged $\geq 60$ years) diagnosed with a chronic illness such as a thyroid disorder is automatically categorized as high risk, with an explanatory note displayed to justify the decision.

This dual-tiered output combining data-driven deep learning with rule-informed reasoning produces diagnostic feedback that is both interpretable and clinically actionable. An example of the generated output panel is provided in Figure 6.6, illustrating how AI-based prediction and rule-based logic jointly inform the risk assessment process.

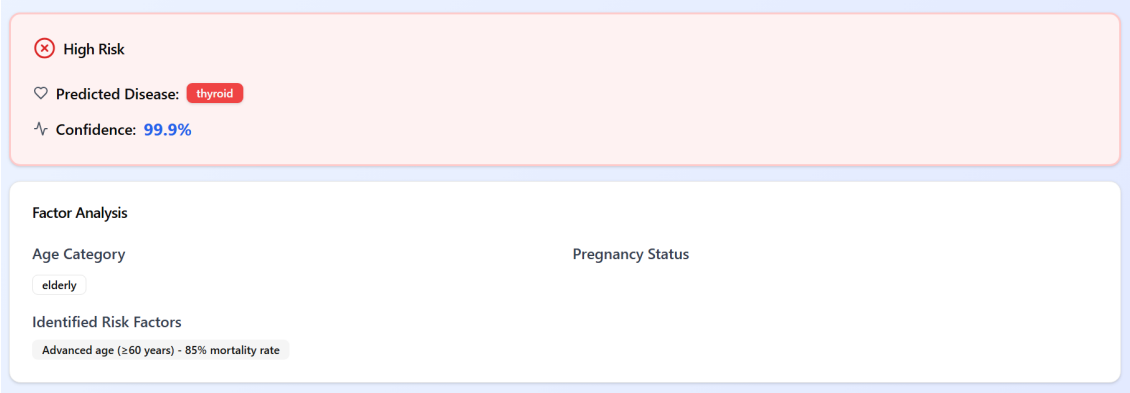



Figure 6.6: System output showing predicted disease class, confidence level, and risk tier with demographic justification.

### 6.9.3 Integrated Explainability via SHAP

To enhance model transparency and user trust, the interface incorporates SHAP (SHapley Additive Explanations) [66], a widely adopted framework for interpreting complex machine learning models. This module provides both global and local interpretability by quantifying each feature's relative contribution to a given prediction, thereby clarizing how the AI system derives its diagnostic outputs.

The resulting explanations are presented through intuitive visualizations that allow clinicians to examine the relative importance of input variables in real time. As illustrated in Figure 6.7, the feature importance chart for a representative thyroid prediction highlights a clear ranking of contributing factors. TSH (thyroid-stimulating hormone) emerges as the dominant feature, normalized to 100% influence, serving as the primary driver of the model's decision. It is followed by T4U (95%), T3 (80%), and age (35%), each contributing progressively less to the final prediction.

This normalized representation of feature importance ensures interpretability by expressing all contributions relative to the most influential variable. Moreover, the observed ranking is consistent with established clinical knowledge, where TSH is recognized as the most critical biomarker in thyroid disorder assessment, followed by complementary hormonal indicators. Such alignment between model outputs and domain expertise reinforces the reliability and clinical relevance of the AI-RiskX system within decision-support environments.

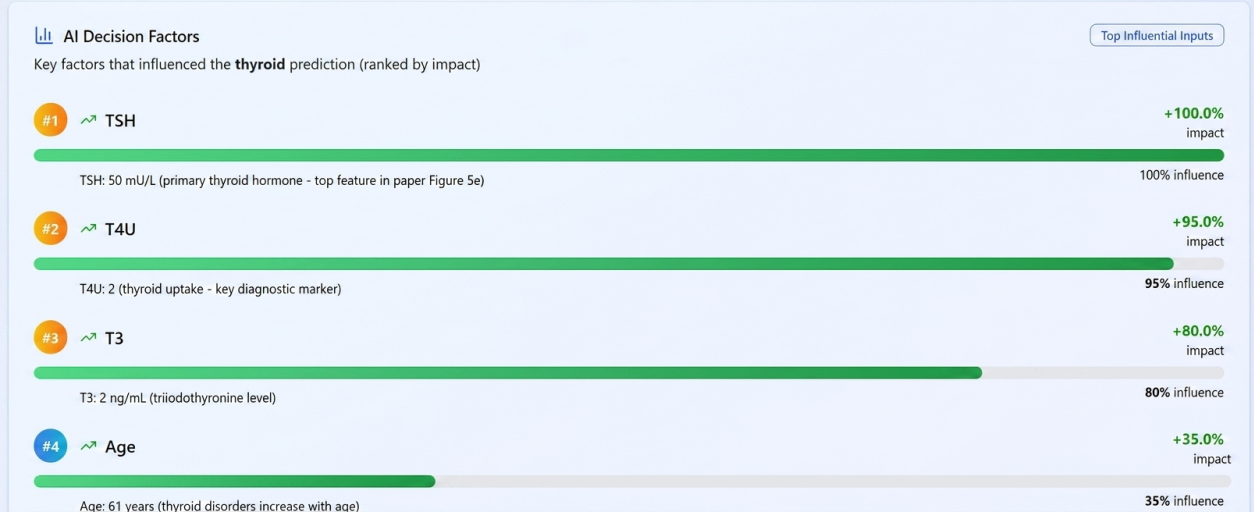



Figure 6.7: Feature importance for thyroid disorder prediction based on SHAP values. (TSH is identified as the most influential factor).

By integrating prediction, reasoning, and explainability into a unified interface, AI-RiskX enhances clinician trust, facilitates informed decision-making, and supports real-world applicability across diverse healthcare settings.

## 6.10 Conclusion

This chapter presented a comprehensive evaluation of the AI-RiskX framework. The CNN–LSTM hybrid model achieved state-of-the-art multidisease classification accuracy and demonstrated superior robustness compared to both traditional and standalone deep learning models. Through ablation and cross-validation analyses, the complementary value of convolutional and sequential modeling was confirmed, while statistical testing validated the significance of performance improvements.

ROC and confusion matrix analyses highlighted near-perfect discrimination across disease classes, and SHAP-based explainability reinforced clinical trust by aligning model decisions

with medical reasoning. Finally, the implemented web interface showcased the system's operational feasibility for real-time, transparent healthcare support.

These results establish AI-RiskX as a key component of the broader AI-LMS ecosystem, providing the intelligent identification and explainability foundation for pandemic-resilient telemonitoring. The next chapter introduces NS-Assist, the decision-support module focused on long-term pediatric nephrotic syndrome management.

# Chapter 7

# NS-Assist: A Pediatric Decision-Support System for Remote Healthcare Management

## 7.1 Introduction

Pediatric chronic kidney diseases, particularly *Idiopathic Nephrotic Syndrome (INS)*, represent one of the most demanding conditions in child healthcare due to their recurrent nature and need for continuous follow-up. Effective management requires precise corticosteroid therapy, regular laboratory testing, and consistent communication between clinicians and families. In low- and middle-income regions, these requirements are often hindered by limited medical infrastructure and geographical constraints, leading to delayed interventions and reduced adherence to treatment plans.

The COVID-19 pandemic further exacerbated these challenges by disrupting hospital operations, restricting in-person visits, and exposing critical gaps in long-term disease supervision. This context underscored the urgent need for resilient, technology-driven solutions capable of ensuring continuity of care for vulnerable pediatric patients.

To address these limitations, this research introduces NS-Assist [119] an intelligent, knowledge-driven decision support and telemonitoring system designed to optimize the management of pediatric INS. Developed in collaboration with pediatric nephrologists from El-Mansoura Hospital (Algeria), NS-Assist integrates clinical expertise, Internet of Medical Things (IoMT) data acquisition, and a transparent rule-based reasoning engine to support early relapse detection, therapeutic adaptation, and home-based monitoring.

Serving as the monitoring component within the AI-LMS framework, NS-Assist bridges the gap between hospital and home environments through explainable, real-time decision support. Its architecture ensures transparent, traceable, and adaptive reasoning, allowing clinicians to maintain active supervision while empowering caregivers with actionable guidance. This chapter presents the conceptual design, implementation, and validation of NS-Assist as a scalable model for intelligent, pediatric-oriented telehealth in both normal and pandemic conditions.

## 7.2 Identified Challenges in the Management of Idiopathic Nephrotic Syndrome (INS)

Idiopathic Nephrotic Syndrome (INS) is a chronic, relapsing kidney condition that primarily affects children and demands accurate [123, 124], long-term clinical oversight. Its recurrent episodes not only complicate medical management but also impact children's psychological health, educational performance, and overall quality of life [125]. These complexities emphasize the need for personalized and adaptive therapeutic frameworks that can accommodate each patient's evolving clinical profile. Effective care thus relies on strong coordination among pediatricians, caregivers, and multidisciplinary medical teams to ensure continuous follow-up, lifestyle adaptation, and dynamic treatment regulation.

A holistic understanding of INS progression requires attention to three critical clinical stages: the initial episode, during which corticosteroid therapy is introduced and intensive clinical supervision begins; the early relapse phase, necessitating swift therapeutic readjustment and close follow-up; and the post-treatment monitoring phase, which focuses on dose tapering, remission validation, and relapse prevention [123, 126]. Each of these stages serves as a decision-making milestone that underpins a structured and evidence-based clinical trajectory.

Interviews conducted with pediatric nephrologists revealed several pressing challenges chief among them the timely detection of relapses, maintaining caregiver engagement, and ensuring consistent long-term follow-up. Recurrent hospital admissions and extended stays disrupt children's normal routines and impose both psychological and financial burdens on families, particularly those distant from specialized healthcare centers. Consequently, developing adaptive, patient-centered management systems is crucial for improving clinical outcomes and sustaining psychosocial stability.

This study underscores the need for resilient, adaptive healthcare strategies in pediatric

nephrology approaches that combine intelligent monitoring, transparent decision support, and collaborative medical coordination to safeguard children affected by INS, even under dynamic and resource-constrained healthcare conditions.

### 7.2.1 Current Treatment Process

The clinical management of Idiopathic Nephrotic Syndrome (INS) generally begins with an initial hospitalization period of approximately two weeks, following the confirmation of diagnosis through clinical signs and laboratory findings. During this early stage, physicians initiate symptomatic therapy to control edema, regulate dietary intake, and conduct continuous daily evaluations under pediatric supervision.

Once the patient achieves medical stabilization, care responsibilities gradually shift from the hospital setting to the home environment. At this stage, parents or caregivers monitor essential physiological indicators such as urine output, weight, and protein levels and record daily test results. Periodic medical reviews are scheduled at regular intervals: initially every two weeks, then extended progressively to monthly and finally quarterly appointments over a follow-up period of about two years. In the case of relapse, the patient is readmitted for treatment adjustments, primarily involving recalibration of corticosteroid dosages and additional clinical supervision.

This coordinated process brings together pediatricians, nursing staff, and nutrition specialists, supported by the active engagement of parents. Despite this structured approach, maintaining continuity of care remains demanding. Recurrent hospital visits and the need for regular supervision can disrupt the family's routine and impose logistical and emotional burdens, particularly for those residing far from tertiary medical facilities. These difficulties become even more pronounced under restrictive conditions such as during pandemics when travel limitations and infection risks interfere with consistent follow-up.

### 7.2.2 Challenges in the Current Process

The clinical management of pediatric Idiopathic Nephrotic Syndrome (INS) involves a set of interconnected challenges that affect both medical teams and families. For caregivers, maintaining reliable home-based follow-up is particularly demanding, especially in rural or hard-to-reach regions. Delays in communicating essential physiological or biochemical measurements often gathered on a weekly basis can postpone therapeutic decisions and heighten the likelihood of disease progression or complications.

Healthcare professionals, on the other hand, face their own obstacles. Among these are the rapid management of acute medical incidents such as infections or thrombotic events, the regulation of concurrent disorders like hypertension, and the ongoing supervision of patients showing steroid dependency or resistance. Each of these elements requires frequent reassessment and flexible therapeutic adjustment.

These already significant burdens became far more severe during the COVID-19 health crisis. Movement restrictions, rescheduled appointments, and infection risks associated with hospital environments disrupted the regular continuum of pediatric care. Both patients and practitioners encountered obstacles in maintaining communication and timely monitoring.

In response, healthcare institutions began introducing digital and adaptive mechanisms such as virtual consultations, continuous physiological monitoring tools, and remote therapeutic supervision to sustain the quality of care and preserve patient safety. The successful integration of these technologies demonstrated their potential to reinforce healthcare systems and ensure continuity even under crisis conditions.

## 7.3 Proposed Solution: NS-Assist

To overcome the limitations identified in the current management of Idiopathic Nephrotic Syndrome (INS), this research introduces the NS-Assist framework an intelligent, knowledge-based clinical support environment designed to improve the long-term follow-up of pediatric patients. Conceived and refined through collaboration with specialists from the Pediatrics Department of El-Mansoura Hospital, NS-Assist is intended to streamline disease supervision by enabling remote observation, automatic notifications, and context-aware medical recommendations.

The system combines the capabilities of the IoMT with a transparent rule-based reasoning core. This decision mechanism allows healthcare providers to monitor patient parameters in real time and receive early alerts when high-risk patterns emerge, such as abnormal protein levels or elevated creatinine concentration.

In situations where physical consultations are limited such as during pandemic outbreaks the platform facilitates virtual triage, helping clinicians identify cases that require immediate attention while reducing unnecessary hospital visits. By merging IoMT-driven physiological data collection with explainable artificial intelligence reasoning, NS-Assist enhances the reliability of clinical decision-making, reinforces patient safety, and ensures the continuity of care under both routine and emergency healthcare conditions.

### 7.3.1 General Architecture of NS-Assist

The NS-Assist platform was conceived to optimize the clinical management of pediatric Idiopathic Nephrotic Syndrome (INS) by integrating intelligent reasoning mechanisms with real-time remote supervision capabilities. The system operates as a comprehensive digital framework that unites medical professionals and caregivers in a shared environment, promoting collaborative diagnosis, dynamic treatment adjustment, and consistent long-term follow-up.

From a deployment standpoint, NS-Assist adopts a hybrid client–server model to ensure scalability and secure communication. At its core lies a decision-making engine built upon two complementary modules a rule-based reasoning unit hosted on a protected web server developed with Spring Boot and linked to a MySQL database.

Clinicians access the platform through a web interface created with ReactJS, which facilitates case management, decision visualization, and therapeutic updates. In parallel, parents and caregivers utilize a Flutter (Dart) mobile application connected to the same backend via RESTful APIs. This design guarantees centralized data synchronization, unified reasoning, and seamless interoperability between the web and mobile environments.

The backend infrastructure encompasses the application's business logic, authentication services, and the modules responsible for data acquisition, knowledge representation, and clinical reasoning. Communication between system components is secured using HTTPS protocols, thereby maintaining the confidentiality and integrity of sensitive medical data throughout the monitoring process. The MySQL database ensures unified and securely synchronized management of patient information. This modular design fosters scalability, facilitates maintenance, and allows the seamless integration of future artificial intelligence extensions.

The NS-Assist framework is structured around three interdependent functional components, each contributing to decision support and continuous patient supervision:

1. **Hospitalization Component:** During inpatient care, medical records are generated and continuously updated with clinical indicators, therapeutic history, and system-generated recommendations. These records guide corticosteroid adjustments and relapse management protocols. Nursing staff collect real-time physiological data such as arterial pressure and urinary composition through IoMT-connected sensors. When abnormal readings are detected, the system automatically issues alerts to prompt immediate medical review and intervention.

2. **Monitoring Component:** After discharge, the system maintains patient follow-up through remote observation. Caregivers and parents input daily physiological indicators, including proteinuria levels and edema status, which are transmitted to the centralized repository. Physicians analyze this incoming data stream to detect potential relapse trends and adjust treatment strategies accordingly. This remote monitoring loop ensures continuity of care beyond the hospital environment.

3. **Knowledge Base:** Serving as the cognitive core of the decision support system, this component encapsulates validated medical rules and pediatric nephrology protocols, such as corticosteroid dosage guidelines (e.g., 60 mg/m$^2$/day during relapse episodes), which support diagnostic and therapeutic reasoning. By integrating real-time IoMT data with this rule base, NS-Assist enables consistent, transparent, and evidence-based decision-making across both hospital and home-monitoring phases. A detailed presentation of the knowledge base is provided in Section 7.3.3.

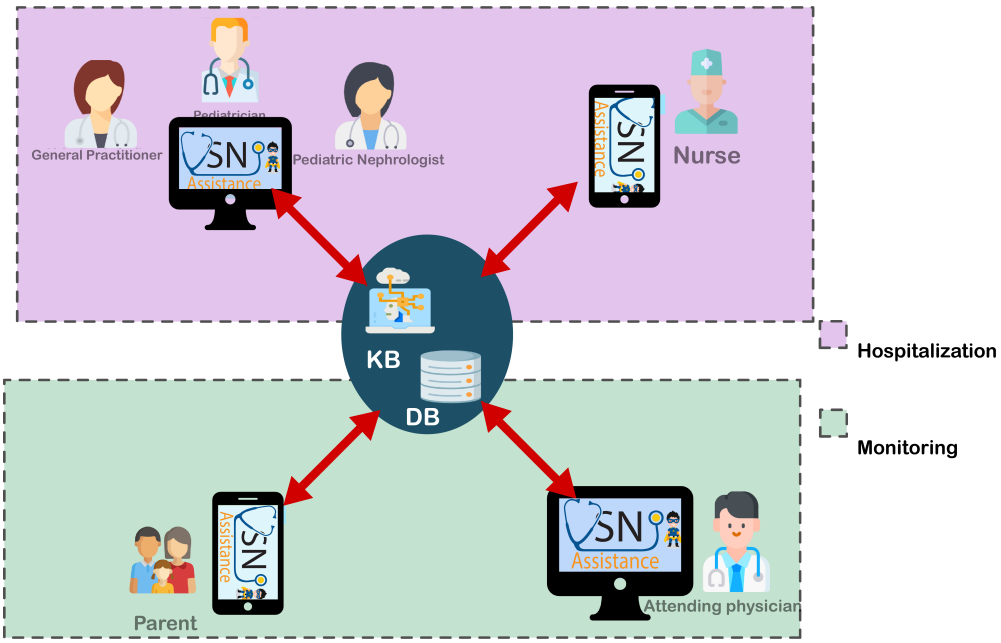



Figure 7.1: General architecture of the NS-Assist system.

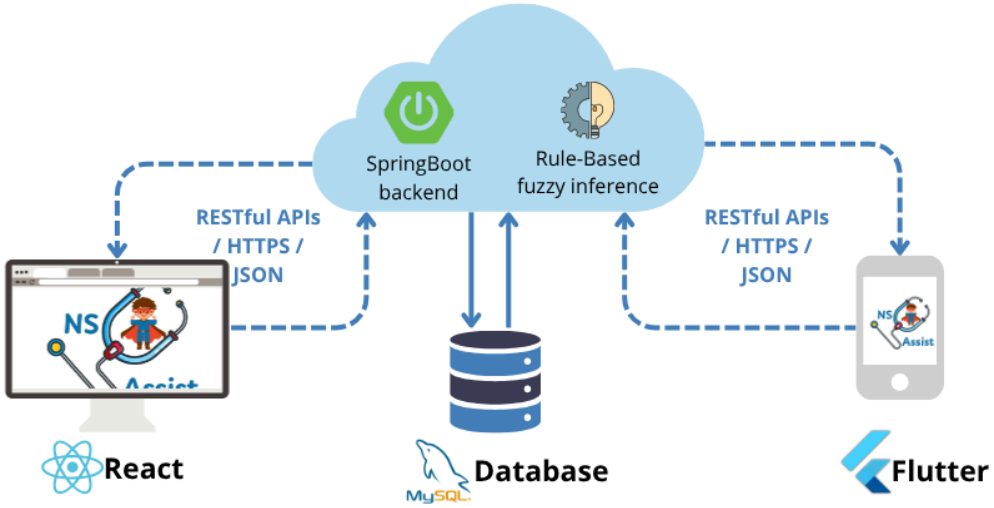



Figure 7.2: Application architecture of the NS-Assist web and mobile platforms.

### 7.3.2 NS-Assist Process

The NS-Assist framework functions as an intelligent, knowledge-based decision-support environment that facilitates collaboration between healthcare providers and patient families throughout both hospitalization and post-discharge follow-up phases. It is designed to enhance coordination, data transparency, and therapeutic responsiveness across all stages of Idiopathic Nephrotic Syndrome (INS) management.

The system serves two distinct user groups: (1) Pediatricians and nephrologists, who access the web portal to manage patient profiles, review analytical outputs, and oversee treatment decisions; and (2) Parents or caregivers, who use the mobile interface to report daily physiological observations and maintain contact with clinical staff. Through its IoMT-integrated sensors, NS-Assist enables continuous data acquisition, ensuring prompt detection of relapse indicators and enabling early medical intervention. As illustrated in Figure 7.3, the system follows four main phases:

1. **Clinical Assessment and Initial Symptoms:** This initial phase begins when signs of illness first appear. NS-Assist organizes the input of biological and clinical parameters into structured digital records, supporting accurate evaluation and therapeutic decision-making by healthcare professionals.

2. **Hospitalization and Clinical Monitoring:** During hospital admission, patient data are continuously updated within the system's centralized repository. NS-Assist tracks

critical metrics and produces alerts for any deviations from normal ranges, thereby enabling physicians to react swiftly to emerging complications or fluctuations.

3. **Home Health Monitoring:** Following hospital discharge, the platform ensures the continuity of follow-up through remote observation. Parents input daily readings such as proteinuria levels, edema status, or blood pressure which are securely transmitted to the main server. The system analyzes these entries in real time to detect early warning signs and guide clinicians toward timely action.

4. **Medical Consultation and Decision Support:** In the decision-support phase, NS-Assist employs its embedded knowledge base to perform rule-based reasoning. The generated recommendations assist physicians in refining diagnoses, optimizing corticosteroid regimens, and managing potential relapses more effectively.

Additionally, the system autonomously issues alerts when critical conditions are inferred. Real-time physiological data are compared with established clinical thresholds, prompting instant notifications to medical teams and caregivers to ensure swift and informed responses.

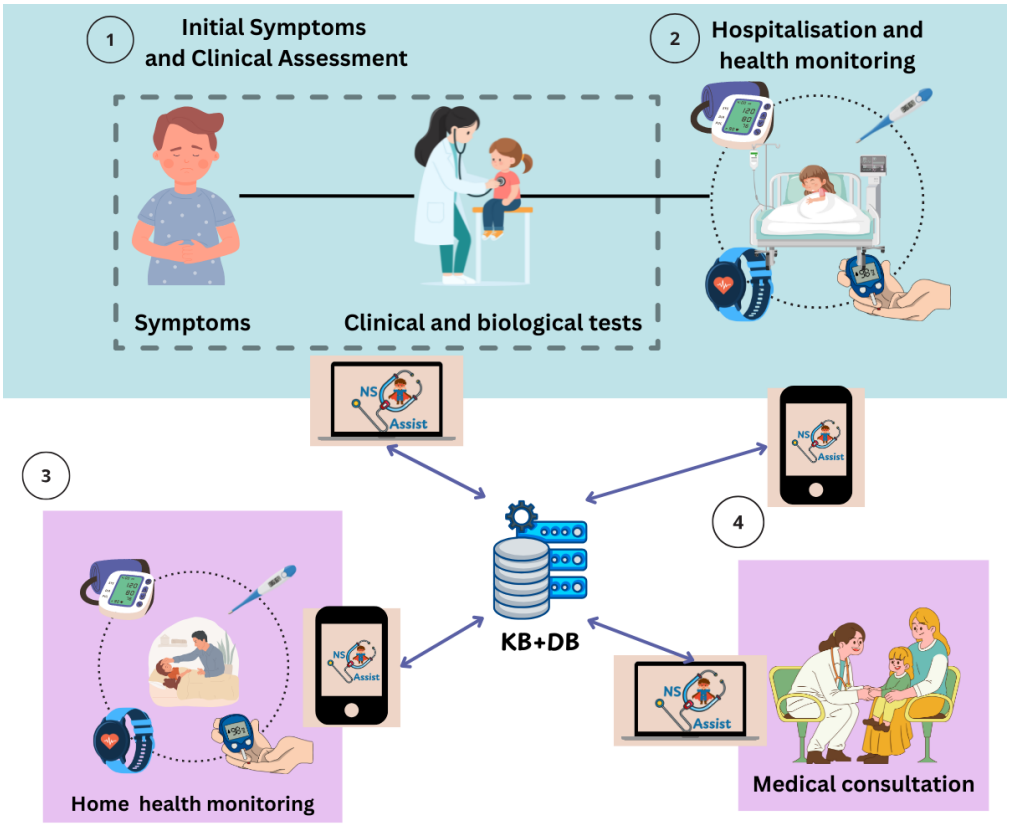



Figure 7.3: Operational process of the NS-Assist system.

### 7.3.3 Knowledge Base

Although recent progress in machine learning has brought powerful predictive and analytical capabilities to healthcare, this research adopts a knowledge-oriented framework rather than a purely data-driven paradigm. This choice reflects the clinical need for transparent and verifiable reasoning processes that align with established medical practice.

A principal advantage of this framework lies in its adaptability. The rule repository can evolve over time as new evidence or updated treatment standards emerge: existing rules may be modified or refined, and novel ones can be incorporated without redesigning the entire system. This flexibility guarantees that the decision-support environment remains medically relevant, consistent with current clinical guidelines, and responsive to continuous scientific progress.

The NS-Assist knowledge component was jointly designed with pediatric nephrology specialists to mirror the therapeutic procedures used in managing Idiopathic Nephrotic Syndrome (INS). The clinical workflow for INS including diagnosis, relapse control, and corticosteroid regulation translates naturally into a rule-based reasoning structure. Representative categories include:

- Diagnostic rules: parameters such as proteinuria level or serum albumin concentration are defined as explicit "IF–THEN" statements determining whether hospitalization or additional diagnostic testing is warranted.
- Escalation logic: cases exhibiting corticosteroid resistance or dependency trigger progressive treatment protocols that escalate toward immunosuppressive therapy.
- Integration of real-world data: by combining live inputs from IoMT sensors with the internal rule base, the system ensures that its reasoning mirrors clinical practice, supports early detection of abnormalities, and promotes confidence among medical professionals.

#### a) Key Attributes of the Knowledge Base

Within the NS-Assist reasoning engine, three main biomarkers serve as the foundation for therapeutic guidance in pediatric Idiopathic Nephrotic Syndrome (INS) management: proteinuria, urine dipstick results, and creatinine concentration [**?**]:

1. **Proteinuria:**

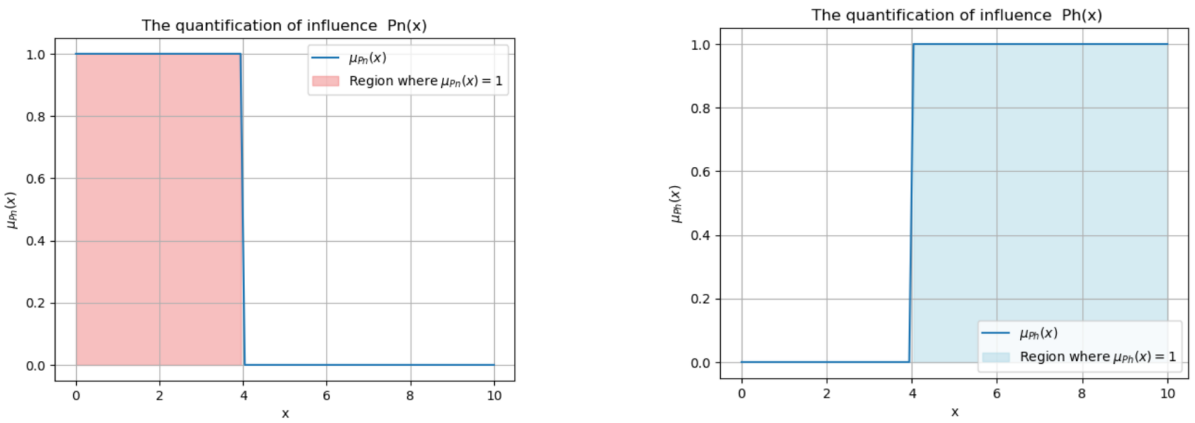
- Reference threshold: values at or below $\leq 4$ mg/m$^2$/h are considered physiologically normal, whereas measurements exceeding this level signal a potential risk of relapse [**?**].
- *Decision rule:*

$$\mu P_n(x) = \begin{cases} 1 & \text{if } x \leq 4 \text{ (normal)}, \\ 0 & \text{if } x > 4 \text{ (abnormal)}. \end{cases} \tag{7.1}$$

  This binary inference Figure 7.4 automatically generates alerts when abnormal protein excretion is detected, prompting the adjustment of corticosteroid therapy (for instance, 60 mg/m$^2$/day).

2. **Urine Dipstick:**
   - A negative $(-)$result indicates an absence of urinary protein, while any positive response (+, ++, etc.) vreveals proteinuria.
   - In the system's rule base, these outcomes are digitally represented as 0 for normal and 1 for abnormal conditions. This binary encoding supports the automated identification of relapse events without manual interpretation.
3. **Creatinine:**
   - Reference range: concentrations between 3 and 8 mg/L are regarded as normal for pediatric patients [136]. Values exceeding 8 mg/L suggest possible renal impairment.
   - These data are likewise codified within the knowledge base 0 for normal and 1 for abnormal to sustain continuous detection of kidney dysfunction and reinforce evidence-driven decision-making.

These clinical rules are embedded within the Decision Support System (DSS), functioning dynamically with real-time data gathered through IoMT-connected sensors. As the platform receives physiological measurements such as blood pressure, proteinuria, and creatinine concentration, it applies predefined logical conditions to identify deviations from normal ranges. Whenever a parameter exceeds its acceptable limit such as an elevation in creatinine the relevant rule is automatically activated, producing a targeted alert and corresponding clinical recommendation for the attending physician.




(a) (b)

Figure 7.4: Proteinuria influence quantification: (a) Membership function $\mu_{Ph}(x)$; (b) Membership function $\mu_{Pn}(x)$.

### b) Knowledge Base Variables and Example Rules

To implement the therapeutic logic governing Idiopathic Nephrotic Syndrome (INS) management, the NS-Assist reasoning module expresses medical expertise through quantifiable variables and structured rule definitions. Each variable represents a measurable physiological or clinical factor, while the rules determine the appropriate therapeutic or diagnostic action to be taken in response to specific input conditions.

These encoded elements collectively represent diagnostic checkpoints, treatment transitions, and decision pathways that emulate physician reasoning within the decision support environment. The following table (Table 7.1) outlines the primary variables forming the foundation of the rule base.

Table 7.1: Variables Defined in the Knowledge Base Framework.

| Variable | Description |
|---|---|
| **D** | Day of treatment or monitoring period. |
| **P** | Proteinuria level measured during follow-up. |
| **Ph** | High proteinuria condition. |
| **Pn** | Normal proteinuria condition. |
| **CT** | Corticosteroid treatment administered to the patient. |
| **Ds** | Discharge event after clinical improvement. |
| **Strip** | Urine dipstick test result. |
| **StripP** | Positive dipstick (protein detected). |
| **StripN** | Negative dipstick (normal). |
| **Rneph** | Referral to a pediatric nephrologist. |
| **Healing** | Recovery confirmation based on clinical assessment. |
| **Urine_Monitor** | Routine dipstick-based monitoring activity. |
| **Remission** | Complete remission achieved and confirmed. |

To demonstrate how the reasoning process functions in practice, the next table provides an illustrative rule set corresponding to the relapse-management phase following treatment completion in pediatric INS care. These encoded rules govern the adjustment of corticosteroid therapy, specialist referrals, and remission validation according to temporal progression and biomarker fluctuations. The structured knowledge representation promotes consistent therapeutic decisions, strengthens clinical supervision, and maintains full conformity with recognized pediatric nephrology guidelines [**?**, 121].

Table 7.2: Therapeutic decision rules applied in the relapse-control stage following treatment of INS.

| No. | Rule Description |
|---|---|
| 1 | **WHILE** P is Ph **THEN** CT is 60 mg/m$^2$/day in a single intake. |
| 2 | **IF** D $\geq$ 1 **AND** D $\leq$ 6 **AND** P is Ph **THEN** CT is 60 mg/m$^2$/day. |
| 3 | **IF** D $>$ 6 **AND** P is Pn **THEN** Ds **AND** CT is 60 mg/m$^2$/day. |
| 4 | **IF** D $<$ 1 month **AND** P is Ph **THEN** Rneph. |
| 5 | **IF** D $>$ 1 month **AND** P is Pn **THEN** CT is 45 mg/m$^2$/every other day. |
| 6 | **IF** D $<$ 2 months **AND** P is Ph **THEN** Rneph. |
| 7 | **IF** D $>$ 2 months **AND** P is Pn **THEN** CT is 30 mg/m$^2$/every other day. |
| 8 | **IF** D $<$ 3 months **AND** P is Ph **THEN** Rneph. |
| 9 | **IF** D $>$ 3 months **AND** P is Pn **THEN** CT is 15 mg/m$^2$/every other day. |
| 10 | **IF** D $<$ 4 months **AND** P is Ph **THEN** Rneph. |
| 11 | **IF** D $>$ 4 months **AND** P is Pn **THEN** CT is 0 **AND** Remission **AND** Urine_Monitor. |
| 12 | **IF** D $\leq$ 2 years **AND** Strip is StripP **AND** P is Ph **THEN** Rneph. |
| 13 | **IF** D $>$ 2 years **AND** Strip is StripN **THEN** Healing. |

## 7.4 Implementation and Functional Modules

This section presents the practical realization of the NS-Assist framework, conceived as an intelligent telemonitoring and clinical-support ecosystem for pediatric Idiopathic Nephrotic Syndrome (INS) management. The implementation integrates two interactive components: (1) a web-based interface dedicated to healthcare professionals, and (2) a mobile application intended for caregivers and parents.

Together, these applications operate collaboratively to sustain continuous, adaptive, and patient-oriented monitoring. The web platform hosts a rule-driven decision-support core, capable of generating context-specific diagnostic insights and therapy recommendations grounded

in established medical guidelines. In parallel, the mobile interface ensures real-time capture of physiological indicators, allowing caregivers to record and transmit health data directly from home.

By unifying these two components, NS-Assist enhances the precision and responsiveness of clinical supervision, promotes adherence to treatment protocols, and ensures continuity of care even under resource constraints or emergency conditions such as pandemic disruptions.

### 7.4.1 NS-Assist Process via the Web Application

The web application represents the central operational layer of the NS-Assist environment, enabling physicians to manage and visualize patient information throughout every phase of the care cycle.

**Clinical Assessment and Initial Symptoms:** Physicians enter clinical observations and laboratory results into structured electronic forms. This data collection step establishes a standardized and traceable digital record for each patient.

**Hospitalization and Clinical Monitoring:** The system aggregates continuous clinical measurements covering indicators of disease progression, relapse probability, and prior treatment responses. The interface presents these aggregated results through intuitive dashboards, assisting clinicians in identifying therapeutic trends and supporting evidence-based decision-making.

**Medical Consultation and Decision Support:** The platform interacts directly with the knowledge-base module, applying rule-based reasoning to generate patient-specific recommendations. These include proposed corticosteroid adjustments, follow-up schedules, and early-warning alerts for potential relapse events.

Collectively, this web-based workflow ensures reliable information management, transparent reasoning, and effective communication between physicians and families foundational elements of the NS-Assist telemonitoring system.

Figures 7.5 to 7.7 depict the principal operational features of the system. Figure 7.5 displays the weekly input interface used to record biological indicators, including proteinuria, creatinine, and urea levels. From these measurements, the Decision-Support System (DSS) performs real-time analytical reasoning to generate diagnostic insights, as illustrated in Figure 7.6. In this module, the framework detects possible relapse trends and proposes corresponding medical actions such as initiating hospitalization procedures when required. Finally, Figure 7.7 highlights the therapy-management dashboard, which automatically suggests the appropriate corticosteroid dosage, frequency, and treatment duration according to

the predefined medical-practice rules and evidence-based guidelines.

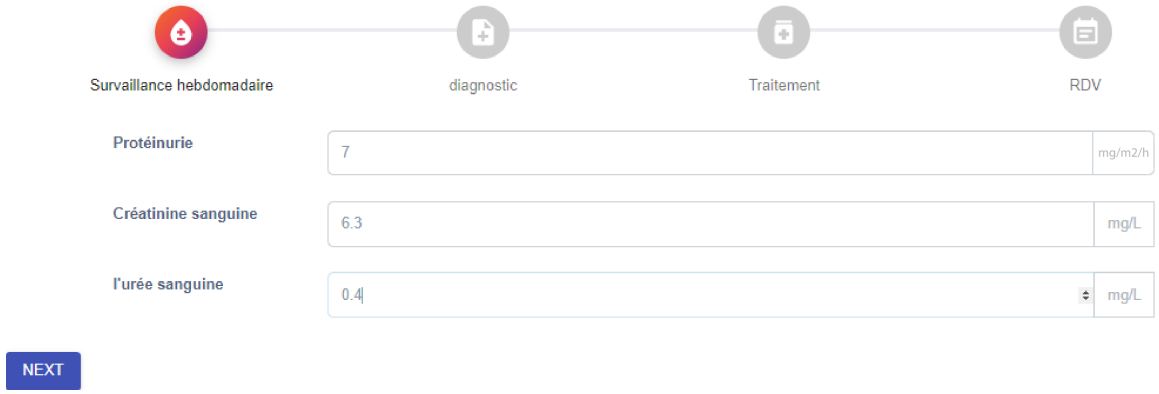



Figure 7.5: Entering medical test results through the clinician interface.

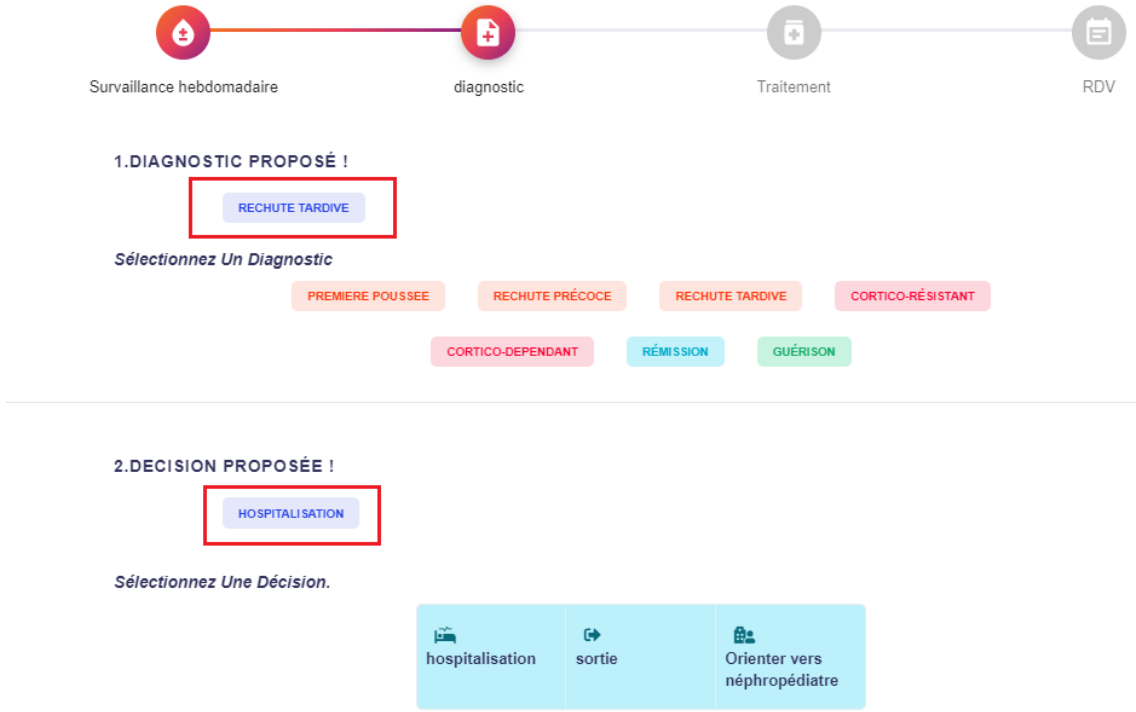



Figure 7.6: Diagnostic suggestions and decision recommendations generated by the DSS.

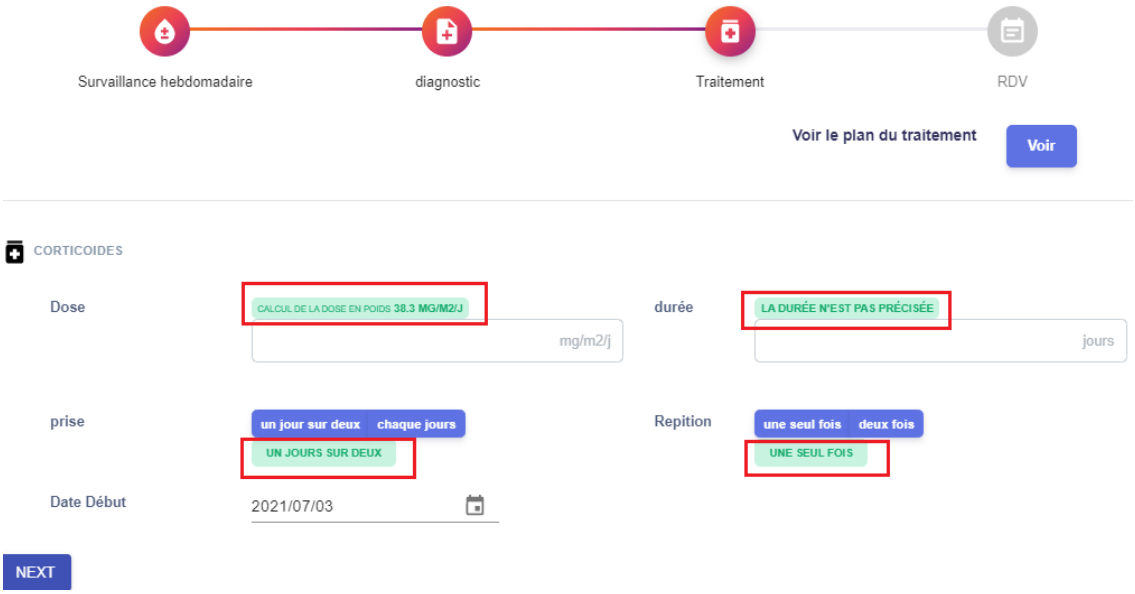



Figure 7.7: Corticosteroid dosage and treatment recommendation interface.

### 7.4.2 NS-Assist Process via the Mobile Application

The mobile application functions as an extension of the web platform, providing seamless and continuous supervision during both hospitalization and home-care periods. During inpatient treatment, healthcare staff and caregivers use the app to log physiological readings such as blood pressure, body weight, and temperature alongside biochemical values including proteinuria and creatinine. When the patient returns home, parents continue using the same interface to record daily updates, which are securely uploaded to the central NS-Assist database in real time.

The decision-support module then interprets the transmitted measurements through its embedded knowledge base, identifying any deviation from the expected range and automatically producing alerts whenever abnormal conditions arise.

As shown in Figure 7.8, the mobile interface enables caregivers to easily enter key health indicators (e.g., systolic/diastolic pressure, temperature, weight, urine-test outcomes, and edema presence). The system continuously evaluates these data streams, forwarding notifications to pediatricians if potential relapse signals such as recurrent edema or elevated creatinine are detected. This two-way communication framework supports proactive case management, continuous monitoring, and rapid clinical response, thereby reinforcing collaboration between families and healthcare providers even beyond hospital environments.

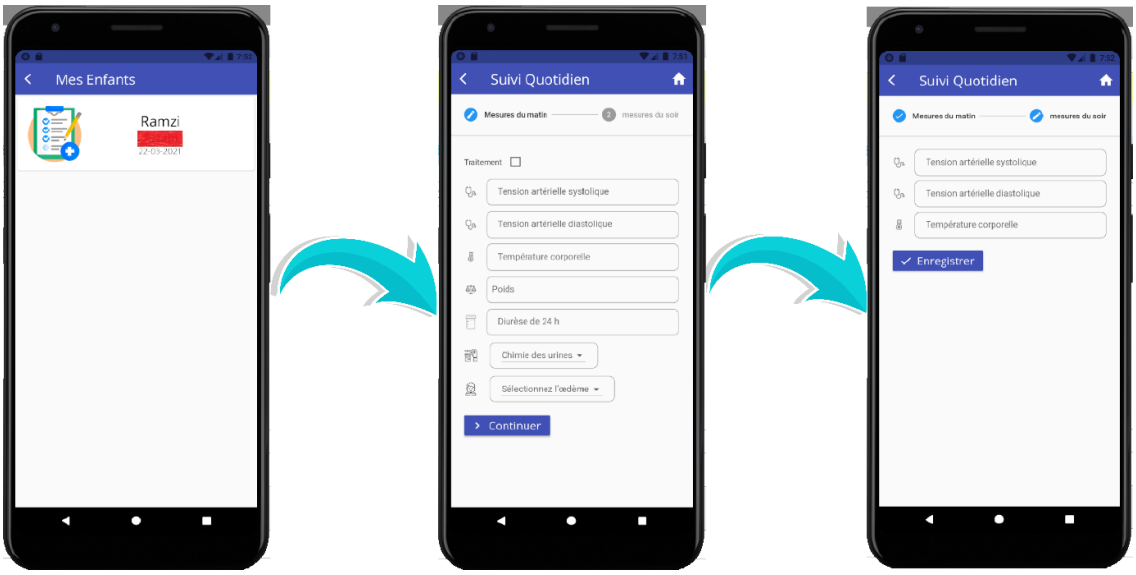



Figure 7.8: Daily home monitoring interface through the NS-Assist mobile application.

## 7.5 System Evaluation and Validation

The performance of the NS-Assist framework was assessed through a combination of field implementation and user-centered studies aimed at measuring its usability, clinical relevance, and contribution to coordinated pediatric care. This evaluation phase involved direct trials with pediatric patients alongside structured qualitative feedback gathered from physicians, nurses, and parents. The goal was to determine the system's effectiveness in facilitating clinical decision-making, optimizing communication, and ensuring safe, efficient follow-up across hospital and home environments.

### 7.5.1 Field Evaluation

The field evaluation of NS-Assist was carried out in partnership with the Pediatrics Department of El-Mansoura Hospital (Algeria). A total of fifteen children diagnosed with Idiopathic Nephrotic Syndrome (INS) in a stable, non-relapsing state participated, together with their families, after providing informed consent. This study followed an observational and descriptive design, concentrating on workflow enhancement and the practical usability of the system. Because the goal was performance validation rather than hypothesis testing, neither randomization nor a control group was required. All clinical data were handled anonymously and in full accordance with ethical research standards.

The investigation examined the variation in clinical workflow durations between conven-

tional management routines and NS-Assist–supported processes. Data visualizations and corresponding figures were generated from feedback collected from physicians and caregivers involved in daily patient follow-up.

In typical stable cases (see Figure 7.9a), the use of NS-Assist reduced the time required for parameter measurement from 2–5 minutes to less than 2 minutes, and shortened physician–parent communication from 5–10 minutes to under 5 minutes, without compromising diagnostic accuracy.

For patients presenting comorbid conditions (Figure 7.9b), time reductions were observed across all workflow stages: data measurement decreased from 5–10 minutes to approximately 2–5 minutes, clinician communication from 5–10 minutes to under 5 minutes, and medical decision formulation from 1–10 minutes to less than 5 minutes.

During relapse management scenarios (Figure 7.9c), efficiency gains were even more pronounced. The duration of parameter acquisition decreased from 5–10 minutes to approximately 2–5 minutes, consultation time from 10–20 minutes to 5–10 minutes, inter-specialist coordination from 5–30 minutes to under 10 minutes, and therapeutic decision-making from 1–10 minutes to less than 5 minutes.

Overall, Figure 7.9 summarizes these outcomes, demonstrating NS-Assist's effectiveness in optimizing pediatric care workflows, improving coordination among healthcare professionals, and accelerating the overall therapeutic response process.

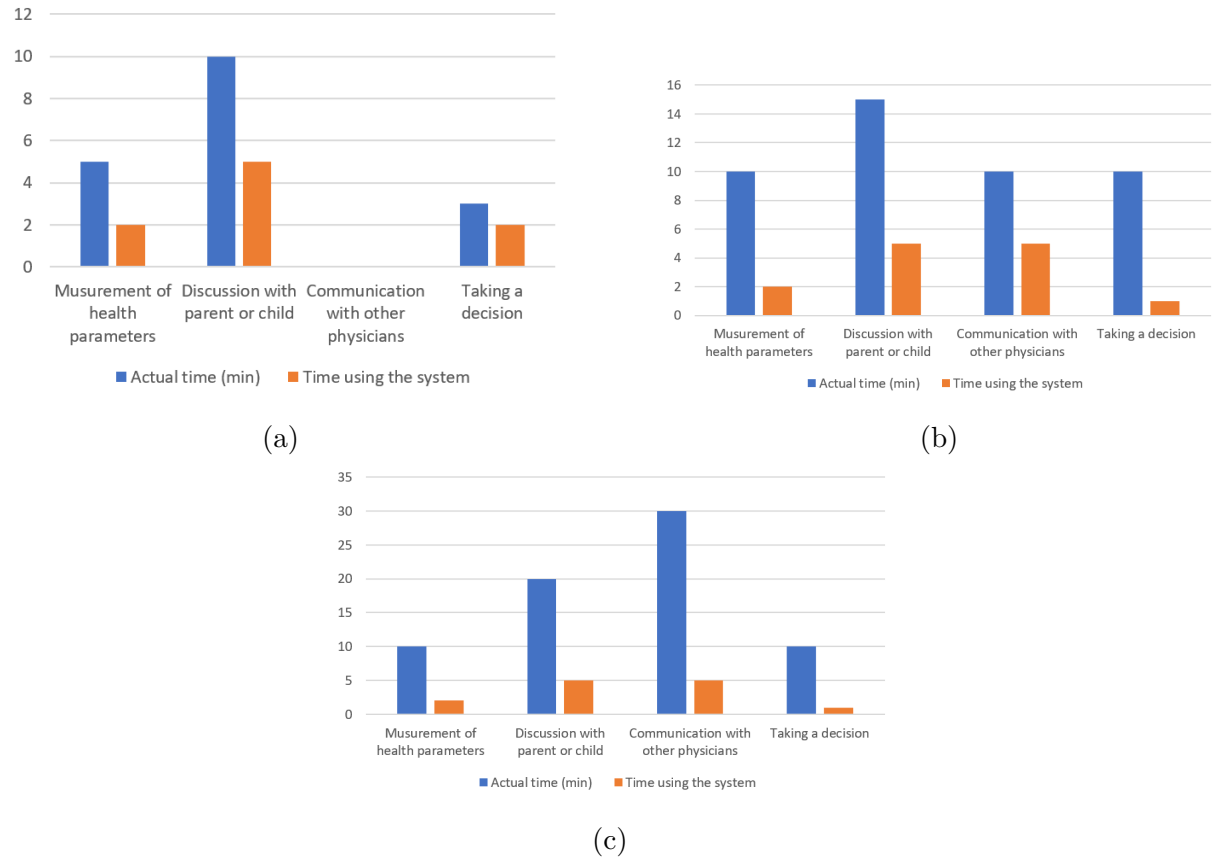



Figure 7.9: Comparison of consultation-time reduction across distinct clinical scenarios supported by NS-Assist: (a) routine follow-up, (b) consultation involving comorbid complications, and (c) relapse management.

### 7.5.2 Survey-Based Evaluation

In addition to the field investigation, a structured questionnaire-based study was administered to 25 healthcare participants (including physicians and medical students) and 15 parents involved in INS care. The survey consisted of 13 questions grouped into four analytical dimensions:

- Interface usability for both clinicians and parents,
- Clinical usefulness and overall contribution to the quality of care,
- Workflow performance and degree of professional coordination, and
- Potential drawbacks, such as financial constraints or reduced direct contact between clinicians and patients.

This evaluation aimed to capture participants' perceived impact of the NS-Assist system on medical decision support, teamwork among healthcare providers, and the broader implementation of patient-centered digital monitoring.

**a) Healthcare Professionals' Feedback**

- **Ease of Use:** Every participant (100%) reported that the clinician interface was clear, intuitive, and easy to navigate.
- **Clinical Utility:** All respondents agreed that NS-Assist improved coordination and enhanced care quality for INS cases, with 93% specifically highlighting smoother collaboration among team members.
- **Innovation:** A large majority (88%) described NS-Assist as an innovative advancement in pediatric healthcare, while 97% praised its capacity for real-time patient monitoring.
- **Traceability:** Complete record traceability was appreciated by 100% of professionals, who emphasized the system's ability to maintain transparent tracking of clinical indicators and patient history.
- **Cost and Time Efficiency:** Approximately 88% observed no additional cost implications, and 90% reported meaningful time reductions in daily clinical procedures.
- **Recommendation:** All respondents confirmed that they would recommend the adoption of NS-Assist within their institutions or professional circles.
- **Personal Interaction:** Half of the participants (50%) expressed a minor concern that increased digitalization could lessen direct clinician–patient interaction.

**b) Parents' Feedback**

- **Ease of Use:** The majority of parents (88%) described the mobile application as clear, convenient, and easy to navigate, emphasizing its accessibility for daily health data entry.
- **Recommendation:** Every respondent (100%) indicated that they would confidently endorse NS-Assist to other families caring for children affected by INS.

Collectively, both user groups expressed strong satisfaction with the system's overall performance, usability, and clinical relevance. These results further validate NS-Assist's effectiveness in pediatric nephrology management, particularly in supporting proactive home monitoring, reducing administrative effort, and strengthening communication channels between caregivers and healthcare providers.

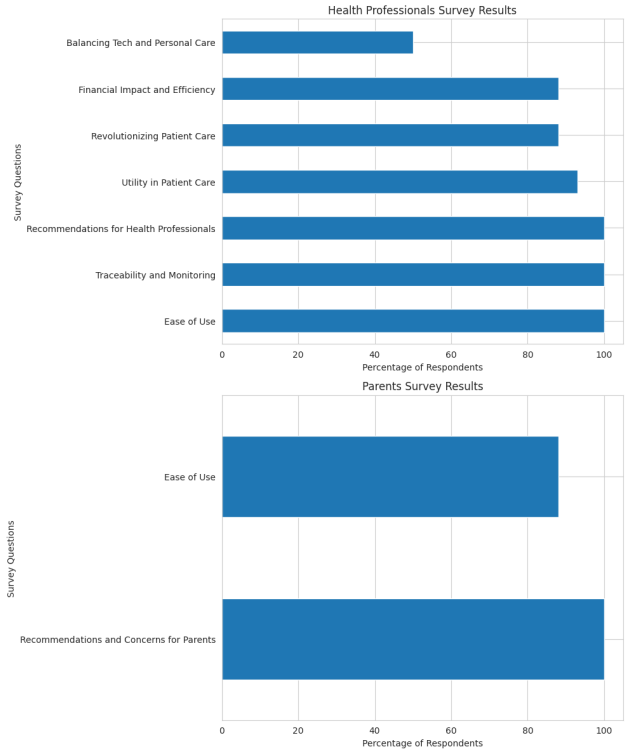



Figure 7.10: Survey responses from healthcare professionals and parents regarding NS-Assist usability and perceived impact.

# Conclusion

This chapter presented NS-Assist, a clinically validated decision-support system for managing pediatric Idiopathic Nephrotic Syndrome (INS). By combining rule-based reasoning and IoMT-enabled data capture, the system bridges medical expertise with intelligent automation to deliver continuous, transparent, and patient-centered care.

Its hybrid web–mobile architecture enables seamless collaboration between clinicians and caregivers, replacing paper-based workflows with an interactive digital environment. Field evaluations with pediatricians and families confirmed the system's usability, reliability, and clinical value, showing reduced consultation time, improved coordination, and enhanced mon-

itoring especially in remote or crisis settings.

Beyond INS, NS-Assist's modular and interoperable design allows adaptation to other chronic pediatric conditions. As part of the broader AI-LMS framework and complemented by AI-RiskX, it demonstrates the feasibility of an intelligent, explainable, and integrated telemonitoring ecosystem. Together, these contributions chart a coherent path toward next-generation healthcare systems that are data-driven, interpretable, and ethically responsible, and they prepare the ground for the reflections and perspectives developed in the General Conclusion.

# General Conclusion

This thesis addressed one of the major challenges highlighted during global health crises: the need for more intelligent, explainable, and sustainable telemonitoring systems capable of maintaining continuity of care under pandemic conditions.

The first part of this thesis established the conceptual and theoretical foundations. It reviewed international pandemic management frameworks, examined the evolution of telemedicine and intelligent healthcare, and analyzed the enabling technologies Artificial Intelligence (AI), Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC) that collectively enable connected, data-driven healthcare infrastructures. The literature review highlighted the predominance of task-specific models (e.g., detection or prediction) and the lack of unified, explainable systems capable of long-term, multidisease supervision.

To bridge these gaps, the second part introduced and validated the main contributions of this thesis, supported by a comprehensive empirical evaluation:

- **AI-LMS: AI-based Long-Term Monitoring System:** A distributed telemonitoring architecture. It supports continuous and scalable patient monitoring during pandemics.
- **AI-RiskX: An Explainable Deep Learning Approach for Identifying At-Risk Patients during Pandemics:** An explainable deep learning framework for multidisease prediction. It combines CNN–LSTM modeling with SHAP explanations.
- **Evaluation and Results of AI-RiskX:** A complete experimental evaluation of the proposed framework. The results demonstrate high accuracy, robustness, and explainability.
- **NS-Assist: A Pediatric Decision-Support System for Remote Healthcare Management:** A rule-based decision-support system for pediatric nephrotic syndrome. It validates the practical use of the proposed monitoring framework.

These contributions collectively form a cohesive and interoperable ecosystem that integrates data-driven intelligence, expert knowledge, and human interpretability. The integration of AI-RiskX's predictive capabilities, validated experimentally, with NS-Assist's clinical reasoning illustrates the transition from theoretical design to practical medical decision-support tools.

From a scientific perspective, this work advances three key areas:

1. The design of a generalizable and scalable architecture for resilient healthcare telemonitoring applicable beyond pandemic scenarios.

2. The development and empirical validation of explainable AI models that enhance clinical trust and ensure ethical transparency.

3. The implementation of a hybrid reasoning paradigm that bridges data-driven deep learning and expert knowledge through complementary AI subsystems.

Beyond its technical contributions, this research reinforces the vision of human-centered and ethically aligned healthcare. By simultaneously addressing explainability, interoperability, and scalability, the proposed ecosystem promotes inclusive care for vulnerable populations—such as children, elderly patients, and individuals with chronic conditions—while ensuring resilience against future public health emergencies.

This work also opens several promising research directions:

- Extending AI-LMS to additional medical domains and diverse patient populations, including rare and under-represented diseases.

- Integrating federated, privacy-preserving, and multimodal learning approaches to enhance secure data sharing across healthcare institutions.

- Strengthening interoperability with international Electronic Health Record (EHR) standards to facilitate seamless clinical integration.

- Expanding validation through multi-center clinical trials and real-world longitudinal deployments.

- Exploring reinforcement learning and adaptive knowledge bases to enable self-optimizing and continuously evolving telemonitoring systems.

In conclusion, this thesis demonstrates that the convergence of Artificial Intelligence (AI), the Internet of Medical Things (IoMT), and Mobile Cloud Computing (MCC), combined with

explainability and domain knowledge, enables the development of intelligent, transparent, and resilient telemonitoring architectures.

The integrated ecosystem composed of AI-LMS, AI-RiskX (along with its validated evaluation module), and NS-Assist represents a significant step toward a new generation of explainable and equitable digital healthcare systems.

It paves the way for future research and interdisciplinary collaboration between computer scientists, clinicians, and policymakers, with the shared goal of building a global, ethical, and sustainable model of intelligent healthcare for the 21$^{st}$ century.

# List of Publications

### Peer-Reviewed Journal Papers

- **N. Zendaoui**, N. Bouchemal, M. R. A. Berkani, M. Bouzahzah, S. Harous, and N Bouchemal *"AI-RiskX: An Explainable Deep Learning Framework for Multidisease Risk Assessment and Telemonitoring in Pandemic Conditions,"* **Bioengineering**, vol. 12, no. 10, Article 1127, MDPI, 2025. DOI: 10.3390/bioengineering12101127

- **N. Zendaoui**, N. Bouchemal, N. Bouchemal, I. Boussebough, and G. Ivanova *"NS-Assist: Nephrotic Syndrome Assistance System for Pediatric Decision-Making in Pandemic Situations,"* **Applied Sciences**, vol. 15, no. 21, Article 11433, MDPI, 2025. DOI: 10.3390/app152111433

### International Conference Papers

- **N. Zendaoui**, N. Bouchemal, and M. Benabdelhafid, *"AI-LMS: AI-Based Long-Term Monitoring System for Patients in Pandemics: COVID-19 Case Study,"* in **Lecture Notes in Computer Science (LNCS)**, vol. 14396, pp. 272–285, Springer, Cham, 2025. DOI: 10.1007/978-3-031-49333-1_20

- **N. Zendaoui**, N. Bouchemal, and Z. Zendaoui, *"Revolutionizing Pandemic Management: A Comprehensive Review and Exploration of Technological Innovations,"* in **Proc. 2023 Third International Conference on Theoretical and Applicative Aspects of Computer Science (ICTAACS)**, Skikda, Algeria, 2023, pp. 1–8. DOI: 10.1109/ICTAACS60400.2023.10449658

### National Conferences

- M. Rebiai, M. R. A. Berkani, I. Besseri, S. Tobbal, B. Bengherbi, and **N. Zendaoui** *"Optimized Cardiac Diseases Identification Technique Through MFCC Analysis of PCG Signals,"* presented at the **2024 National Conference on Artificial Intelligence in Electrical Engineering (NCAIEE'2024)**, Yahia Fares University of Médéa, Médéa, Algeria, 2024.

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