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Maple Health AI: Intelligent Precision Health Startup for Canada

Dr. Husna Maryam

Department of Precision Health Cumming School of Medicine, University of Calgary, Alberta, Canada

Correspondence: Dr. Husna Maryam, Final Year Specialization Student, Department of Precision Health Cumming School of Medicine, University of Calgary, Alberta, Canada, Email: husna.maryam@ucalgary.ca

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Abstract

Healthcare systems in Canada continue to face persistent challenges arising from fragmented health data, limited interoperability across jurisdictions, and delays in clinical decision-making. Patient information is frequently distributed across electronic health records, laboratory systems, genomic repositories, medical imaging platforms, wearable technologies, and patient-generated lifestyle data, limiting clinicians' ability to construct comprehensive and longitudinal patient profiles. These structural limitations contribute to delayed diagnoses, suboptimal treatment selection, preventable hospital readmissions, and rising system-level costs. This paper introduces MapleHealthAI, a conceptual national precision health platform designed to integrate multimodal health data within a secure, artificial intelligence–enabled ecosystem. The proposed framework leverages predictive, classification, and recommendation models, combined with natural language processing, to support early risk detection, personalized treatment guidance, and automated clinical insights embedded within routine clinical workflows. Emphasis is placed on augmenting clinical decision-making through explainable, clinician-facing decision support rather than autonomous automation, aligning with established principles for trustworthy and responsible artificial intelligence in healthcare [4]. MapleHealthAI addresses jurisdictional data silos through an interoperability-focused architecture and privacy-preserving machine-learning approaches, including federated learning and differential privacy. The framework is designed to align with Canadian regulatory and governance requirements for health data protection and software as a medical device, including federal and provincial privacy legislation and emerging artificial intelligence governance frameworks [8-9], [12]. Although empirical validation is required, MapleHealthAI offers an ethically grounded, policyaligned blueprint to advance an equitable, secure, and scalable precision health infrastructure in Canada. The framework provides a practical conceptual foundation for future pilot studies, crossjurisdictional collaboration, and responsible clinical translation of federated artificial intelligence in precision medicine.

Introduction

Modern healthcare delivery remains constrained by fragmented information ecosystems that impede timely diagnosis, coordinated care, and individualized treatment planning, particularly for patients with complex chronic and rare diseases. Clinical data are frequently dispersed across electronic health records, laboratory information systems, genomic repositories, medical imaging platforms, and patient generated wearable technologies. This fragmentation limits clinicians' ability to synthesize comprehensive and longitudinal patient profiles, contributing to prolonged diagnostic timelines, inefficient treatment selection, increased healthcare expenditures, and persistent inequities in patient outcomes [1].

Precision medicine has emerged as a promising paradigm for addressing these challenges by tailoring diagnostic and therapeutic strategies to individual biological, clinical, and environmental characteristics. Advances in pharmacogenomics have demonstrated the potential to improve medication selection and reduce adverse drug events by accounting for genetic variation in drug metabolism and response, particularly in psychiatry and pain management where inter-individual variability is substantial [2,3]. In parallel, artificial intelligence (AI) methodologies have enabled more sophisticated risk stratification, pattern recognition, and clinical decision support across diverse healthcare applications. Despite these advances, real-world implementation of precision medicine remains limited. Persistent data silos, privacy concerns, inconsistent interoperability across jurisdictions, and insufficient integration of advanced analytics into routine clinical workflows continue to constrain adoption and impact. Regulatory bodies increasingly emphasize the need for transparency, safety, and governance in AI-enabled healthcare systems, particularly for software classified as a medical device. In Canada, Health Canada's guidance outlines expectations related to accountability, lifecycle management, and clinical risk mitigation [4]. At the health-system level, large-scale initiatives such as Alberta Health Services' Connect Care illustrate both the opportunities and complexities associated with embedding advanced analytics within existing clinical infrastructures [5].

Together, these challenges underscore a critical gap between the growing availability of precision-health data and the health system's ability to integrate, govern, and translate these data into timely clinical insight. Addressing this gap requires a unified, privacy-preserving, and interoperable framework capable of supporting advanced analytics while remaining aligned with clinical workflows and Canadian regulatory requirements.

Federated learning has gained attention as a privacy-preserving approach that enables collaborative model development across distributed institutions without centralized data aggregation. In this context, this narrative review synthesizes literature on pharmacogenomics, AI-enabled clinical decision support, federated learning, healthcare interoperability, and rare disease diagnostics to propose MapleHealthAI, a conceptual federated artificial intelligence framework designed to support precision medicine in Canada. The framework emphasizes multimodal data integration, explainable decision support, privacy preservation, and regulatory alignment, providing a policyrelevant blueprint for future research, pilot implementation, and cross-jurisdictional collaboration.

Background and Related Work

Precision Health and Pharmacogenomics

Precision medicine adapts healthcare interventions to inter-individual biological, environmental, and behavioral differences. Pharmacogenomics represents one of the most mature applications of this paradigm, offering evidence-based guidance on how genetic variation influences drug metabolism, efficacy, and toxicity. Clinical implementation guidelines developed by the Clinical Pharmacogenetics Implementation Consortium (CPIC) demonstrate how gene–drug relationships can inform medication selection and dosing in routine practice [2].

Despite strong evidence, adoption of pharmacogenomics remains inconsistent. Barriers include limited clinician familiarity, insufficient integration of genomic data into electronic health records, and the absence of real-time decision support. While commercial pharmacogenomic tools have shown promise, particularly in psychiatry, challenges related to scalability, transparency, and workflow integration persist [3].
Similar implementation gaps are observed in rare disease diagnostics, where genomic sequencing results are often generated in specialized laboratories but returned to clinicians as static reports that are not integrated with phenotypic or longitudinal clinical data. As a result, clinicians must manually reconcile genetic findings with fragmented patient histories across multiple systems, contributing to delayed diagnoses and reduced clinical utility of otherwise actionable genomic information.

Artificial Intelligence in Clinical Decision Support

AI methods have been increasingly incorporated into clinical decision support systems to assist clinicians with diagnosis, risk stratification, and treatment planning. Machine-learning approaches have demonstrated utility in identifying complex patterns within structured and unstructured clinical data, including free-text notes analyzed using natural language processing. However, many AI tools remain narrowly scoped or poorly integrated into clinical workflows, limiting their real-world impact.

Successful deployment of AI-enabled decision support requires not only technical performance but also interpretability, workflow alignment, and clinician trust. Evidence consistently emphasizes that decision-support tools should augment, rather than replace, clinical judgment and be delivered at the point of care.

Rare Disease Diagnosis and Data Fragmentation

Patients with rare diseases frequently experience prolonged diagnostic delays due to phenotypic heterogeneity, limited clinical awareness, and fragmented access to clinical and genomic data. International initiatives highlight the importance of collaborative data sharing and integrative analytic approaches to reduce diagnostic timelines and improve outcomes [1].

AI-based pattern recognition and knowledge-graph methods have shown promise in rare-disease diagnostics, particularly when multimodal data are available. Nevertheless, privacy concerns and institutional data silos continue to hinder large-scale collaboration.

Federated Learning and Privacy-Preserving AI

Federated learning enables distributed model training across institutions while retaining data locally, sharing only model updates for aggregation. This paradigm has gained prominence in healthcare as a means of supporting cross-institutional collaboration while maintaining compliance with privacy and data-governance requirements. Recent research has explored fairnessaware federated learning approaches to mitigate bias and promote equitable model performance [6,7].

Despite its advantages, federated learning introduces challenges related to system complexity, communication overhead, and governance. Effective implementation requires robust validation, monitoring, and accountability mechanisms.

Regulatory and Health-System Context

Regulatory authorities increasingly classify AI-enabled clinical applications under software-as-amedical-device frameworks, emphasizing transparency, risk management, and post-deployment oversight. In Canada, Health Canada's guidance outlines expectations related to safety, accountability, and lifecycle management for such systems [4].
At the system level, platforms such as Connect Care demonstrate the importance of interoperability standards, including FHIR, in enabling scalable digital health solutions and supporting AI integration into clinical workflows [5].

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Conceptual Framework: MapleHealthAI

Framework Overview

MapleHealthAI is a conceptual federated AI framework designed to integrate multimodal patient data and deliver precision-medicine decision support within routine clinical workflows. The framework prioritizes privacy preservation, ethical governance, and interoperability to enable responsible deployment across healthcare systems.

Multimodal Data Sources

The framework integrates multiple data modalities, including genomic data relevant to pharmacogenomics, structured electronic health record data, medical imaging features, and wearable or patient generated physiological and behavioral data.

Federated Learning Architecture

MapleHealthAI employs a federated learning architecture in which models are trained locally at participating institutions and aggregated centrally without transferring raw patient data. This approach enables collaborative learning while preserving patient privacy and institutional autonomy.

Ethical Governance and Bias Mitigation

Ethical considerations are embedded throughout the framework, including transparency, auditability, role-based access controls, and bias-mitigation strategies. Fairness-aware learning approaches are incorporated to reduce disparities in model performance across populations.

Interoperability and Clinical Workflow Integration

The framework emphasizes standards-based interoperability, including FHIR-aligned interfaces and embedded decision support, to ensure seamless integration with existing electronic health record systems and clinical workflows.

Illustrative Use-Case Workflow

Toillustrate practical applicability, consider a pharmacogenomics use case in a clinical setting. A patient with multiple prior medication failures undergoes pharmacogenomic testing through a regional laboratory, while relevant clinical history, medication records, and adverse drug events are stored across disparate electronic health record systems. Within the MapleHealthAI frame work, these data are analyzed locally at the institutional level, and model updates contribute to a federated learning process without sharing raw patient data. The resulting decision-support output is delivered directly within the clinician's existing workflow, highlighting gene-drug interactions and evidence-based medication considerations with transparent rationale. This workflow demonstrates how MapleHealthAI supports clinical decision-making by integrating advanced analytics into routine care without disrupting established processes or compromising data privacy [2,3,4,6].

Methods

Study Design

This study was conducted as a narrative review combined with conceptual framework development. A narrative review was selected as the most suitable approach given the study's objective of synthesizing interdisciplinary clinical, technical, and policy literature to inform conceptual framework design rather than quantitatively evaluating intervention effectiveness. No primary data collection, experimental validation, or human-subjects research was performed.

Literature Search Strategy

Peer-reviewed literature, clinical guidelines, and policy documents were identified through structured searches of Google Scholar and PubMed, focusing on publications between 2015 and 2025 related to precision medicine, pharmacogenomics, AI in healthcare, federated learning, rare disease diagnosis, and clinical decision support.

Evidence Synthesis

Findings were synthesized thematically to identify recurring challenges, enabling recommendations that MapleHealthAI framework.

Ethical and Regulatory Considerations

Ethical and regulatory considerations were incorporated with explicit attention to the division of responsibilities between federal and provincial jurisdictions in Canada. Federal frameworks governing artificial intelligence and digital health technologies, including privacy legislation and guidance for software as a medical device (SaMD), inform requirements related to safety, accountability, and lifecycle oversight [8,9,4]. In parallel, provincial health information legislation governs the collection, use, and disclosure of personal health information within healthcare delivery settings. Accordingly, the proposed framework aligns with relevant provincial statutes, including Ontario's Personal Health Information Protection Act, Alberta's Health Information Act, and Québec's Act respecting the protection of personal information [10-13].

Discussion

The MapleHealthAI framework illustrates how federated artificial intelligence and multimodal data integration couldaddress persistent challenges in precision medicine at a conceptual level. By aligning pharmacogenomics, clinical data, imaging, and patient-generated data within a privacy-preserving architecture, the framework responds to well-documented limitations associated with fragmented care and delayed clinical decision-making, without presuming operational deployment or clinical readiness.

Existing evidence suggests that AI-enabled pharmacogenomic decision-support approaches may improve treatment selection and reduce adverse drug events, particularly in psychiatry and pain management, when appropriately validated and integrated into clinical workflows [2,3].

Similarly, prior studies indicate that AI driven analytic methods have the potential to shorten diagnostic timelines in rare-disease contexts when supported by collaborative, multi-institutional data-sharing strategies [1]. These findings provide a rationale for exploring federated, multimodal approaches but do not imply established clinical effectiveness.

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Federated learning offers a promising conceptual mechanism for enabling such collaboration while maintaining compliance with privacy, security, and governance requirements. Prior research indicates that federated architectures can support cross-institutional model development while reducing risks associated with centralized data storage and enabling fairness-aware learning under controlled conditions [6,7].

Clinical integration remains a critical consideration for future investigation. Alignment with interoperability standards and regulatory guidance is essential to inform responsible design, evaluation, and potential translation of AI-enabled decision-support frameworks, rather than immediate clinical adoption [4,5].

Limitations

This study has several important limitations. First, it is based on a narrative synthesis of existing literature and does not involve primary data collection, experimental validation, or prospective clinical evaluation. As such, the proposed MapleHealthAI framework should be interpreted strictly as a conceptual model rather than a validated clinical system.

Second, heterogeneity within the reviewed literature, including differences in study populations, data modalities, healthcare settings, and evaluation methodologies, limits the ability to draw quantitative conclusions regarding performance, effectiveness, or cost efficiency. Third, key implementation challenges were not empirically assessed. These include data quality variability, institutional readiness, workforce capacity, and resource constraints, as well as the practical complexity of deploying interoperable systems across provincial and territorial healthcare jurisdictions with differing governance structures, digital maturity levels, and health information policies. Such factors may substantially influence real-world feasibility and scalability.

Finally, regulatory and ethical considerations related to AI-enabled healthcare systems continue to evolve. While the proposed framework aligns with current Canadian guidance, future policy developments may necessitate additional safeguards, validation requirements, or design adaptations. Collectively, these limitations highlight the need for rigorous, ethics-approved pilot studies, prospective clinical evaluations, and longitudinal monitoring prior to any consideration of broader system-level translation.

Future Directions

Future research should focus on staged, ethics-approved evaluation pathways to assess the feasibility and responsible translation of federated AI-enabled precision health frameworks. Key priorities include:

- Pilot studies: Conduct small-scale, ethics-approved pilot studies within controlled clinical environments to assess technical feasibility, data integration workflows, and clinician usability without clinical reliance.
- Fairness evaluation: Evaluate model performance across diverse patient populations to identify and mitigate potential biases, ensuring equitable decision-support behaviour across demographic and clinical subgroups.
- Economic assessment: Perform health economic and cost effectiveness analyses to examine resource implications, sustainability, and potential system-level value under realistic implementation constraints.
- Regulatory alignment: Engage with regulatory and policy stakeholders to ensure ongoing alignment with evolving Canadian governance frameworks, interoperability standards, and software-as a-medical-device requirements.

Conclusion

This narrative review and conceptual framework highlights the potential of federated artificial intelligence to advance precision health in Canada. MapleHealthAI provides an ethically grounded, privacy-preserving, and policy-aligned blueprint for integrating AI into Canada's digital health ecosystem.

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Ethical Approval: This study did not involve human participants or primary data collection and did not require ethical approval.

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