Architecting a Co-Designed Clinical Decision Support System for Diabetes Management

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Abstract

Diabetes mellitus, particularly Type 2 diabetes (T2D), imposes a substantial and inequitable burden on New Zealand, with domestic communities disproportionately affected. Early prediction of diabetes complications using machine learning (ML) has shown strong potential, yet most models remain disconnected from real-world clinical workflows and health information systems. This study outlines a co-design and design science research (DSR) programme to develop a machine learning–enabled clinical decision support (CDS) framework for predictive diabetes management in the Waikato region. Working with Health New Zealand (HNZ) Waikato, clinicians, and health informaticians, the research proceeds through three stages: situation awareness of current diabetes management processes, co-design of a data-driven CDS architecture, and evaluation via predictive performance metrics and process simulation. Expected contributions include an empirically grounded CDS framework tailored to local clinical and cultural contexts, improved predictive capabilities for T2D complications and resource planning, and a scalable pathway toward AI-enabled diabetes services that support health advancement and health equity.

CCS Concepts

• **Applied computing**; • **Life and medical sciences**; • **Health care information systems**;

Keywords

Clinical Decision Support, Predictive Diabetes Management, Co-Design, Design Science Research, Machine Learning

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1 Introduction

Diabetes mellitus has emerged as a global epidemic, characterised by chronic hyperglycaemia and associated with microvascular and macrovascular complications that impose a large burden on individuals, families, and health systems (Erandathi et al., 2024). In New Zealand, approximately 348,500 people are living with diabetes, and the vast majority have Type 2 diabetes (T2D) (Health New Zealand, 2024). At the individual level, T2D is strongly associated with complications such as cardiovascular disease, retinopathy, neuropathy, and nephropathy, which diminish quality of life and increase utilisation of hospital and primary care services (Erandathi et al., 2024). For clinicians working in busy clinical environments, decision-making is complicated by uncertainty about disease trajectories, variation in patient responses to treatment, and limitations in information systems that do not fully support predictive risk assessment or population-level planning (Wang et al., 2022).

The proliferation of digital health data, through electronic health records (EHRs), disease registries, and health information exchanges, has enabled the application of ML methods to predict the onset and progression of diabetes-related complications (Çubukçu et al., 2024). Recent systematic reviews identify sets of clinical, laboratory, and demographic features (e.g., HbA1c, lipid profiles, age, ethnicity, duration of diabetes) that are consistently useful predictors of complications such as nephropathy, neuropathy, and

cardiovascular events (Erandathi et al., 2024). These advances have motivated interest in ML-enabled clinical decision support systems (CDSS) that can deliver risk scores, alerts, and treatment recommendations at the point of care. However, as Sutton et al. (2020) note, the success of CDS depends not only on predictive performance but also on usability, workflow integration, governance, and alignment with local health system priorities. In practice, many ML-based systems remain proof-of-concept models and are not embedded in clinical workflows or decision-support environments (Wang et al., 2022).

Within New Zealand, the challenge is compounded by long-standing inequities in diabetes prevalence and outcomes. Domestic communities experience higher rates of T2D (particularly Māori) and its complications, often alongside limited access to culturally appropriate, continuous, and coordinated care (Chepulis et al., 2021; Chepulis et al., 2023). Addressing these inequities requires more than technical innovation: it calls for meaningful engagement, co-design, and careful integration of new tools into existing service pathways (Keenan & Carryer, 2024). This study responds to this need by focusing on the Waikato region and working in partnership with HNZ Waikato, clinicians, and health informaticians to create an AI-enabled CDS framework that can support both individual-level decision-making and system-level resource planning (Wang et al., 2022; Jiang et al., 2024).

2 RELATED LITERATURE

2.1 Clinical Decision Support Systems

Clinical decision support systems (CDSS) are software applications designed to enhance clinical decision-making by integrating patient-specific data with clinical knowledge, guidelines and predictive models (Sutton et al., 2020). CDSS may take the form of reminders, alerts, diagnostic suggestions, risk scores, order sets or care pathways embedded within EHR environments. A widely cited overview by Sutton et al. (2020) concludes that CDSS can improve quality, safety and efficiency in a range of clinical domains by supporting more consistent guideline adherence and more timely recognition of clinical risks. However, the same literature highlights important risks and limitations. CDSS that generate excessive or poorly targeted alerts may contribute to alert fatigue, cognitive overload and eventual workarounds or system bypassing (Sutton et al., 2020). Implementation studies and systematic reviews emphasise that benefits depend critically on alignment with clinical workflows, usability, data quality and organisational readiness, rather than on algorithmic performance alone (Mebrahtu et al., 2021; Grechuta et al., 2024). When CDSS are not well integrated with EHR systems or do not reflect local practice patterns, they may have limited impact on patient outcomes despite high theoretical potential.

In diabetes care specifically, earlier reviews and meta-analyses have shown that CDSS can improve process-of-care indicators and, in some cases, intermediate outcomes such as HbA1c, but the effect sizes are often modest and confidence in the evidence is constrained by small sample sizes, heterogeneity and risk of bias (Jia et al., 2019; Heselmans et al., 2020). These findings motivate a shift from viewing CDSS as purely technical artefacts to understanding them as socio-technical interventions that must be carefully tailored and evaluated within specific health-system contexts.

2.2 Predictive Diabetes Management

Predictive diabetes management (PDM) refers to the use of advanced analytics, artificial intelligence (AI) and machine learning (ML) to forecast clinically relevant events in diabetes care so that interventions can be anticipatory rather than reactive. The underlying premise is that, by transforming rich longitudinal data into short- and long-term risk estimates, clinicians and patients can optimise therapy before deterioration occurs, instead of responding only after hyperglycaemia, hypoglycaemia or complications have developed (Klonoff, 2017; Guan et al., 2023).

Current research in PDM can be broadly grouped into two interrelated areas. The first is short-term glucose forecasting, typically over a 30-60-minute horizon, which is critical for day-to-day self-management and the prevention of acute glycaemic excursions. Early work used linear and autoregressive models, but recent systematic reviews show that deep learning architectures, especially recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, now dominate the field (Zhu et al., 2021; Langarica et al., 2024; Ghimire et al., 2024). These models learn non-linear dependencies between CGM trajectories, insulin dosing, meal intake and physical activity, and many studies report mean absolute error metrics that approach thresholds considered acceptable for clinical decision support. At the same time, comparative evaluations highlight challenges related to generalisability across datasets, vulnerability to data gaps and sensor noise, and the need for clearer standards in evaluation and reporting (Tsichlaki et al., 2022; Zale et al., 2022). The second major strand concerns long-term prediction of diabetes-related complications and adverse outcomes. Here, PDM leverages EHR and registry data, including laboratory results, comorbidities, medications and demographics, to estimate individual risks of nephropathy, retinopathy, cardiovascular disease and other micro- and macrovascular complications over multi-year horizons. ML models such as random forests, gradient boosting and deep neural networks have been shown to predict incident complications with good discrimination, often outperforming traditional risk scores (Dagliati et al., 2018; Jian et al., 2021; Huang et al., 2022). Reviews of AI for diabetes prevention and complication prediction underline the potential of these approaches to support targeted screening, treatment intensification and population-level risk management, while also noting recurrent limitations such as weak external validation, limited calibration assessment and under-representation of high-risk subgroups (Gosak et al., 2022; Fagherazzi et al., 2019).

From an information systems perspective, most PDM studies still evaluate predictive models in isolation from the clinical information infrastructures in which they would operate, with relatively little attention to how these models are integrated into CDSS, data pipelines and organisational workflows to support routine decision-making and service planning.

2.3 CDSS in Predictive Diabetes Management

Research at the intersection of CDSS and predictive diabetes management examines how predictive models, whether rule-based or ML-based, are embedded into decision-support tools that clinicians can use in routine practice. Several reviews have focused specifically on CDSS in diabetes. Huang et al. (2023) summarise the

clinical applications of CDSS in diabetes care and report that many systems target insulin dosing, medication management, screening and monitoring, with evidence of improvements in guideline adherence and certain process measures, but limited and heterogeneous evidence on long-term clinical outcomes and physician-patient experience. Tlili et al. (2024) conduct a systematic review of CDSS for antidiabetic drug management and conclude that these systems can support more appropriate prescribing and glycaemic control, while also emphasising gaps in reporting of harms, cost-effectiveness and patient-centred outcomes.

Several primary studies demonstrate how predictive models are integrated into CDSS architectures for diabetes. Pichardo-Lowden et al. (2021, 2022) describe a real-time CDSS for inpatient glycaemic management that detects dysglycaemia and inappropriate insulin use based on EHR data and notifies clinicians; their quasi-experimental evaluation shows reductions in hyperglycaemia, hypoglycaemia and length of stay in hospital settings. Other work has proposed dashboard-like CDSS that integrate EHR-based risk stratification with visual analytics to support chronic T2D management in primary care and outpatient clinics, demonstrating improvements in process indicators and intermediate metabolic outcomes (Sim et al., 2017; Frontoni et al., 2020).

More recently, ML-based CDSS have been developed for specific predictive decision problems. Ying et al. (2025) report on a randomised clinical trial of an ML-assisted insulin titration CDSS for adults with T2D, showing that the system improved time to optimal dosing and glycaemic control compared with standard care. Thomsen et al. (2025) similarly find that an ML-based CDSS for basal insulin titration can address clinical inertia and provide a user-friendly, efficient tool in outpatient diabetes clinics. Nimri et al. (2025) evaluate a decision-support tool for self-managed insulin dosing in individuals with type 1 diabetes and show that it is feasible, safe and associated with improved glycaemic control. Collectively, these systems illustrate how predictive algorithms can be operationalised within CDSS to support concrete tasks such as insulin titration, perioperative glycaemic management and risk-stratified monitoring.

Despite these advances, reviews of diabetes-specific CDSS note that many systems remain single-site prototypes, highly tailored to local infrastructure and often evaluated in relatively small, homogeneous samples (Heselmans et al., 2020; Jia et al., 2019). Furthermore, even when predictive models are embedded into CDSS, there is often limited reporting on integration with existing hospital information systems, on how clinicians interact with and interpret risk outputs, and on how these tools influence resource allocation or broader care pathways. Emerging commentaries also emphasise that AI-based CDSS may inadvertently reproduce or exacerbate inequities if they are developed from biased data or deployed without explicit attention to under-served groups (Grechuta et al., 2024; Gosak et al., 2022).

2.4 Research Gaps

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Within this body of literature, three gaps are particularly salient for the present study. First, while there is substantial evidence that ML models can predict T2D complications with reasonable accuracy, far fewer studies examine how these models are translated into operational CDSS that are tightly integrated with real-world clinical workflows and information systems (Choi et al., 2023; Wang et al., 2022; Jiang et al., 2024). Second, although equity and fairness are increasingly recognised as critical concerns, empirical evaluations of ML-CDSS in relation to Indigenous or minority populations remain scarce, especially in health systems like New Zealand where diabetes-related inequities are pronounced (Gosak et al., 2022). Third, existing work rarely provides detailed accounts of the socio-technical design processes through which stakeholders' needs, organisational constraints, and equity goals are translated into concrete CDSS architectures and implementation strategies. Addressing these gaps requires not only advances in predictive modelling, but also systematic attention to integration, workflow alignment, and equity-oriented system design, issues that are taken up in the methodological approach described in Section 3.

3 COMPUTER CODE

The research employs a DSR methodology that is tightly coupled with co-design processes. The methodological approach can be conceptualised as a three-stage cycle: situation awareness ("As-Is"), system design ("To-Be"), and evaluation ("Confirm") (Hevner & Chatterjee, 2010; Wang et al., 2022). Each stage is informed by relevant literature and conducted in collaboration with clinical and community stakeholders.

In the situation awareness stage, the study first undertakes a structured review of literature on diabetes management processes, ML-based prediction for T2D, and CDS integration in hospital and primary care settings (Sutton et al., 2020; Çubukçu et al., 2024). Building on this foundation, the research team engages with stakeholders including HNZ Waikato data engineering teams, clinicians within the Waikato AI Health Research Group, and members of the University of Waikato Diabetes and Nutrition Research Centre. Through hui, workshops, and semi-structured interviews, the team maps current diabetes management workflows, from diagnosis through monitoring and treatment, and identifies key decision nodes, bottlenecks, and resource demands. These interactions also explore the existing data storage structures for diabetes records and the availability and quality of EHR variables relevant to predictive modelling, such as HbA1c trajectories, comorbidities, and demographic factors (Chepulis et al., 2021; Erandathi et al., 2024). The outcome of this stage is a detailed "As-Is" process framework that captures both clinical and information system perspectives, including inequities experienced by Te Whatu Ora Waikato, clinicians' patients (Chepulis et al., 2023; Keenan & Carryer, 2024).

The system design stage then focuses on developing the "To-Be" data-enabled CDS architecture. Using historical EHR data supplied by HNZ Waikato under appropriate ethical and governance approvals, the team will construct and train ML models, using frameworks PyTorch, to predict the likelihood of complications and estimate survival probabilities for patients with T2D (Paszke et al., 2019; Erandathi et al., 2024). Ethnicity, age, HbA1c levels, and other clinically relevant variables identified in prior systematic review work and the situation awareness analysis will be used as

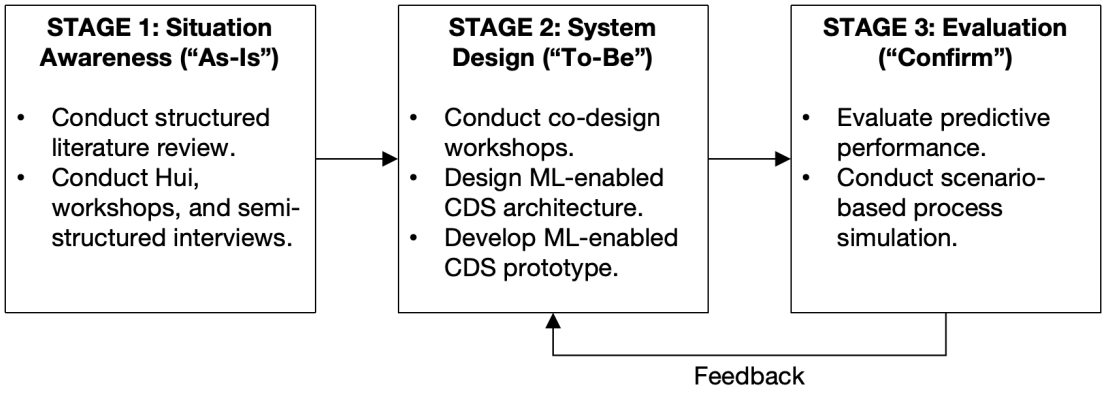


Figure 1: The Research Methodology Framework

candidate features. The CDS architecture will be designed to integrate these predictive models with existing clinical information systems, offering risk scores and decision-support outputs that can be accessed within routine workflows (Wang et al., 2022; Jiang et al., 2024). Architecture design activities include defining data pipelines, specifying interfaces for clinicians and health informaticians, and embedding requirements for privacy, security, and real-time performance. Co-design workshops will be used throughout this stage to ensure that the architecture, user interactions, and presentation of risk information are acceptable, interpretable, and clinically meaningful for medical services and diabetes management (Slattery et al., 2020; Keenan & Carryer, 2024).

The evaluation stage, corresponding to the "Confirm" phase in DSR, involves both technical validation and socio-technical assessment. On the technical side, predictive performance will be evaluated using receiver operating characteristic (ROC) curves and related metrics for diagnostic tests and prognostic models, following best practices outlined by Zou et al. (2007). Additional analyses will examine calibration, subgroup performance across ethnic groups, and potential algorithmic biases (Alowais et al., 2023). On the socio-technical side, process simulation will be conducted using tools such as AnyLogic or Simio to model alternative diabetes management pathways under the proposed CDS framework, with a focus on resource utilisation, waiting times, and monitoring intensity (Jones-Konneh et al., 2018; Jiang et al., 2024). Scenario-based simulations will enable estimation of potential cost savings and service improvements prior to full-scale implementation. Clinicians, primary care providers, and Te Whatu Ora Waikato, health professionals will then be invited to evaluate the feasibility, perceived usefulness, and challenges of the proposed CDSS, providing feedback that will inform iterative refinements to both the predictive models and the overall architecture (Wang et al., 2022; Chepulis et al., 2023).

Across all three stages, the methodology is designed to be iterative and reflexive, allowing insights from evaluation and stakeholder feedback to loop back into earlier stages of design. This aligns with DSR's emphasis on relevance and rigour, as well as co-design's commitment to authentic partnership with end-users and communities (Hevner et al., 2004; Slattery et al., 2020).

4 EXPECTED CONTRIBUTIONS

The project is expected to generate contributions in four interrelated domains: theoretical knowledge, practical system design, health equity and health advancement, and future research pathways.

From a theoretical perspective, the study will articulate a co-designed CDS architecture that explicitly integrates ML prediction capabilities with Indigenous health perspectives and national health service contexts. By grounding system design in both DSR principles and co-design practices, it will demonstrate how predictive analytics, process modelling, and stakeholder engagement can be combined into a coherent framework for AI-enabled health service design (Hevner & Chatterjee, 2010; Slattery et al., 2020). The resulting process maps and decision frameworks for T2D management in the Waikato region will contribute to the broader literature on chronic disease management, health system integration, and information systems for healthcare (Chepulis et al., 2021; Wang et al., 2022).

In terms of practical system design, the project aims to deliver a validated CDS prototype for predictive diabetes management within HNZ Waikato. This includes ML models trained on local EHR data, a reference architecture for integrating these models with existing clinical information systems, and simulation evidence on how the CDS framework may improve monitoring workflows and resource planning (Jiang et al., 2024). The prototype will provide concrete insights into technical, organisational, and governance challenges that must be addressed when moving from theoretical ML models to operational CDSS, thus offering guidance for other regions and health systems considering similar deployments (Sutton et al., 2020; Alowais et al., 2023).

For health equity, the project's co-design approach is central. The CDSS is being designed to support more personalised, proactive management of T2D for patients with different backgrounds, while respecting values and clinical realities in the domestic communities (Keenan & Carryer, 2024). The resulting predictive tools and process frameworks have the potential to improve early identification of high-risk individuals, support culturally appropriate interventions, and ultimately reduce disparities in diabetes outcomes (Chepulis et al., 2023). At the institutional level, enhanced predictive capabilities could help policymakers refine resource allocation plans and design

services that are more responsive to the needs of communities and other population groups facing barriers to care (Health New Zealand, 2024; Mustafa et al., 2024).

Finally, the project is designed as an activation activity that will seed further research and funding. The outputs, including the CDS framework, predictive models, simulation results, and strengthened relationships with HNZ and clinical partners, will form the foundation for a subsequent HRC project grant application, as well as related PhD theses and postdoctoral work in digital health and information systems (Wang et al., 2022; Jiang et al., 2024). Future research could extend the CDS framework to manage complications such as cardiovascular disease, apply similar architectures to other chronic conditions, develop patient-facing mobile applications for self-management, and conduct longitudinal evaluations of system impact on clinical outcomes, patient experience, and health equity metrics across New Zealand (Chepulis et al., 2020; Chepulis et al., 2023).

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