Research Proposal Presentation

Research Methods and Professional Practice (January 2025)

Word count: 2334

Video record:

https://youtu.be/p2hLUDzFzCs

Transcription

Slide 1 - Title

Good afternoon, everyone. I welcome your attendance today. My name is Andrew, and I am glad to introduce the research proposal which examines the "Non-Invasive Glucose Monitoring (NIGM) System: Machine Learning-Based Calibration and Predictive Models Based on Multi-Sensor Data". A study designed to resolve diabetic management problems through innovation in non-invasive blood sugar monitoring, using advanced machine learning approaches and multi-sensor data.

Slide 2 – What is problem?

Let me begin with a story. A 10-year-old child diagnosed with Type 1 diabetes requires finger pricks several times daily to regulate their blood sugar. Patients do not test their blood sugar enough because of discomfort that results in dangerous blood sugar level fluctuations. This affects millions who reside throughout the world. The routine needle procedures by people with diabetes must be done four to six times per day, resulting in 1815 per year and 18000 stabs throughout a decade (ElSayed et al., 2024). The repetitious practice of self-harm results in lower patient adherence because too much physical pain coupled with mental strain makes people skip their blood tests (Uhl et al., 2023). Invasive monitoring of diabetes increases patient discomfort and creates practical difficulties, which produce poor diabetes control and elevated complications risks (Roglic, 2016).

Slide 3 – What is problem?

Diabetics need continuous glucose monitoring to prevent severe complications, as unmanaged blood sugar remains unsafe for health. Excessively high blood glucose levels trigger microvascular and macrovascular damage, resulting in retinopathy, which leads to blindness along with neuropathy that causes amputations and stroke, according to Alghamdi et al (2021) and Ceriello et al (2022). The condition of being hypoglycemic places patients at risk for seizures, together with coma and death (Seaquist et al., 2013). The protection of acute and chronic risks requires the establishment of reliable monitoring methods to keep glucose between 70–180 mg/dL according to clinical guidelines (ElSayed et al., 2023).

Slide 4 – Background

Studies indicate that diabetes affects 830 million people worldwide, which represents 8.5 percent of the global population (WHO, 2024; Klein, 2023). The diagnosis rate increased to 830 million from 200 million in 2019. The global diabetes case numbers are projected to reach 1.3 billion within the next 25 years unless countermeasures are taken. The occurrence of Type 1 diabetes represents 5-10% of diabetes cases, with Type 2 diabetes being responsible for 90% of cases and its causation links to lifestyle and obesity statistics (WHO, 2024). Better prevention measures and management solutions require immediate implementation because the present situation is critical.

Slide 5 – Significance of study

To address these challenges, this research aims to develop advanced machine learning models for calibration and prediction based on multi-sensor data and multi-sensor information to enhance the performance of a non-invasive glucose monitoring system. This research proposal has the potential to revolutionize diabetes management and allow patients to monitor their glucose levels easily, painlessly, and conveniently. The significance of this research is its multidisciplinary nature. It involves biomedical engineering, machine learning, and data science to solve a critical healthcare problem (Patel & Shah, 2021).

Slide 6 – Research questions

The primary question of this research revolves around how machine learning based calibration and prediction models can improve the accuracy and reliability of non-invasive glucose monitoring systems with multi-sensor data. To answer this, we will engage in several secondary questions:

- Firstly, we want to identify the most efficient machine learning algorithms for processing multi-sensor data in non-invasive glucose monitoring systems. This question helps to determine which computational methods are best suited for integrating multiple and non-linear sensor inputs like optical and thermal signals against blood glucose levels (Bhajane et al., 2024).
- Secondly, we want to identify the optimal methods to enhance calibration models for handling person-specific variations and external elements. The measurements obtained through non-invasive glucose monitoring methods are influenced by variations in personal skin structures as well as hydration levels and metabolic patterns (Sun et al., 2024). The question seeks to resolve existing

limitations among calibration methods regarding individual-specific adjustments.

- Lastly, we seek to detect the main obstacles which prevent the implementation of Machine learning-based non-invasive glucose monitoring systems in real-world scenarios. One of the issues to address in translating laboratory validated models into clinical practice is sensor drift, motion artefacts and interoperability with healthcare systems (Nyiramana, 2024). This question is an important check that the research is well aligned with the need for practical realization.

With the help of these questions, we have built our research methodology and it ensures that our findings will be scientifically rigorous and practically applicable. The goal is to fill the gap between theoretical developments and practical utilization of non-invasive glucose monitoring systems (Singh & Berretti, 2024) by addressing these questions.

Slide 7 – Aims and objectives

The purpose of this research is to design and develop a Machine Learning Based framework of an accurate and trustworthy non-invasive glucose monitoring system through multi-sensor data. To achieve this, we have stated the 5 key objectives.

1. Evaluate currently available non-invasive glucose monitoring technologies on the market and determine the deficiencies and ways to make the technology more efficacious.
2. Preprocess multi sensor data such as optical, thermal, and electrochemical signals.
3. Develop and train calibration and prediction models using a machine learning model.

4. Validate developed models by comparing their performance with existing results of methods.
5. Integrate the best-performing models and design a prototype non-invasive glucose monitoring system.

These research objectives establish a specific path that will enable investigation into theoretical and practical components of non-invasive glucose monitoring systems (Rahman et al., 2024).

Slide 8 – Key literature

This research is based on five pillars of literature for their relevance to the interdisciplinary nature of the non-invasive glucose monitoring systems:

- The first pillar focuses on optical and electrochemical glucose sensors which experience limited accuracy due to skin interference along with environmental factors (Bhajane et al., 2024; An et al., 2023). Reliable non-invasive monitoring requires successful resolution of these difficulties.
- The second pillar demonstrates machine learning algorithms that process complex biomedical data according to Rangayyan and Krishnan (2024) and Zamani et al (2024). The signal processing capabilities of convolutional neural networks and recurrent neural networks receive skilled support from multi-sensor fusion techniques, which boost precision according to Patel & Shah (2021) and Rajesh Hanni et al (2024). Glucose monitoring accuracy depends heavily on optimal method optimization.
- The third pillar of multi-sensor data fusion will help to review the problem of reconciling multiple disparate signals into a unified estimate of glucose. As Hussain et al. (2024), Jiang and Ke (2024) highlight, techniques for fusing

heterogeneous sensor data are critical for non-invasive glucose monitoring systems.

- The third pillar investigates calibration models depicting inadequate outcomes of static calibration approaches because they do not adapt to physiological and environmental changes (Zanon et al., 2013; Moses et al., 2024). A dynamic machine learning-based calibration system developed to overcome accuracy limitations should include individual difference understanding (Villena Gonzales et al., 2019).
- The final section of the diabetes management literature review examines research about enhancing patient results through non-invasive glucose monitoring systems. This portion demands a solid background discussion on clinical requirements for AI-based diabetes treatment and patient-involved procedures as described in Nomura et al. (2021) and as Joshi and Kor (2024) emphasize patient-centred technology significance.

These research pillars serve as an appropriate selection because they systemically complete all aspects of non-invasive glucose monitoring devices by covering technical execution and computational processing as well as clinical integration.

Slide 9 – Methodology

The research methodology follows a five-phase process utilizing mixed-methods for creating a non-invasive glucose monitoring system that meets clinical requirements.

Phase 1: Literature Review and Stakeholder Needs Assessment.

A mixed-methods approach is used to analyse the deficiencies in non-invasive glucose monitoring equipment. Two online surveys directed at diabetic patients alongside clinicians have been chosen since they allow for quantitative assessment of usability issues regarding device comfort and accuracy expectations (ElSayed et al., 2023).

Public dataset analysis, such as clinical trials, includes statistical assessment to offer objective measurement of current non-invasive glucose monitoring technology without small-sample study bias (Habehh & Gohel, 2021). The research uses stakeholder interview sessions to identify specific difficulties with device calibration problems in current medical equipment. Recent advancements and limits from a thematic literature review allow researchers to develop their work from verified findings rather than repeating previous methods (Villena Gonzales et al., 2019).

Phase 2: Data Preprocessing and Requirements Finalization.

The second phase of the research methodology merges two approaches for improving data quality and finalizing system requirements through data preprocessing methods. Quantitative approaches establish methods to process multi-sensor data by reducing noise while detecting outliers and extracting features before using statistical techniques to identify predictive variables for glucose measurement, according to Chen et al. (2022). Professional workshops and stakeholder evaluation sessions are used for validating the usability and clinical applicability, and technological rationality of the system to meet specific end-user requirements (Rodriguez-Calero et al., 2020). When both approaches unite their outcomes, they produce final technical and functional requirements that serve as a strong base for subsequent model development.

The Model Development phase 3 works on building and optimizing predictive models through Machine Learning algorithms that process preprocessed multi-sensor data. Regression-based and ensemble methods from machine learning algorithms receive training to build associations between non-invasive sensor data and blood glucose readings through cross-validation approaches (Bian et al., 2024). The model performance obtains improved accuracy along with robustness by employing hyperparameter optimization algorithms based on grid search and Bayesian optimization (Pfob et al., 2022). Optimal models get selected while using mean absolute error and Clarke Error Grid analysis for assessment because they maintain clinical value (Clarke, 2005). This phase represents a vital phase which transforms theoretical requirements into a practical predictive system through data-driven solutions for non-invasive glucose monitoring.

During the Model Validation phase 4, the researcher will apply repeated testing to machine learning models of the non-invasive glucose monitoring system to prove their clinical integrity alongside stability. A benchmark analysis which merges traditional regression algorithms along with existing non-invasive glucose prediction models enables the evaluation of performance metrics according to Zhang (2024). Multiple physiological conditions, including different skin types, hydration levels and motion artefact occurrence, are part of robustness tests that determine how well models generalize among populations (Rodriguez-Calero et al., 2020). The system diagnostic accuracy is validated through statistical root mean square error and correlation coefficients combined with Clarke and Parkes Error Grid clinical acceptability tests (Patel et al., 2023). A cross-dataset evaluation process helps confirm system consistency on external patient groups after model application, thus reducing the risk of overfitting problems (Rajkomar et al., 2019).

Research methodology culminates in performance testing of the developed prototype through technical assessment and user acceptability examination. The system reliability metrics of quantitative assessments consist of testing real-world measurement consistency and long-term stability, and comparing accuracy against invasive blood glucose measurements (Rodbard, 2017). The qualitative assessment includes structured usability tests which engage end-users who have diabetes to evaluate device ergonomics and interface intuitiveness, and overall user experience according to Wiklund et al. (2016). The design process includes empirical evidence from testing and user-focused insights that allow continuous improvements, leading to clinical accuracy expectations and practical use requirements for the system.

Slide 10 – Ethical considerations and risk assessment

This research involves critical issues of ethics. Before doing any data collection or clinical trials, we will obtain permission from relevant ethics committees. Compliance with the General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA) and other data privacy regulations will ensure that data privacy is guaranteed. All participants will give informed consent and we will do whatever is necessary to avoid discomfort and we will use the non-invasive methods (Min et al., 2025).

We have also noted some risks, such as biased inferences, data breaches, and discomfort to the participants. In order to tackle these risks, we will perform strict testing, have utmost cybersecurity systems in place and will make sure that all procedures will be non-invasive and pleasant for the participants. The research will be done ethically and responsibly through these measures.

Slide 11 – Artefacts

The three key artefacts resulting from this research are:

- Calibration and Prediction machine learning models: We will build and document the calibration and prediction machine learning models with its architecture, training approach, and the performance metrics.
- A functional prototype integrating the developed models will be designed to serve as a prototype Non Invasive Glucose Monitoring System capable of real time glucose monitoring.

- Curated Dataset: A multi sensor glucose monitoring dataset will be curated, shared and available to aid in further advancements in this field.

This research's success will be shown by these artefacts and they will also serve as useful resources for future studies.

Slide 12 – Timeline

Our proposed timeline spans six months, with each phase carefully planned to ensure timely completion.

- Phase 1: Conduct a literature review and gather data. The estimated duration is one month, with a primary focus on evaluating essential research articles and existing datasets.
- The data preprocessing along with the feature engineering, Phase 2 has an estimated duration of two months that overlaps with Phase 1. Automated data preprocessing should be prioritized while featuring 10-15 relevant clinical variables.
- Phase 3: The entire model development phase will need two months to complete. Starting with pre-trained models allows faster training time in the development process. Focus on 1–2 high-potential models.
- Phase 4: The entire testing phase requires an estimated duration of one month. You should use synthetic data to perform critical tests when you have restricted access to real-world data.
- Phase 5: Prototype development of a minimal viable product will take about one and a half months. Leverage existing hardware platforms for rapid integration.

- The production of final reports takes one month during phase 6. Full coherence, along with editing and final submission, marks the completion of writing activities which started at the beginning of the academic project.

This timeline ensures that we have sufficient time to address any challenges that may arise while maintaining a steady pace toward our goals.

In conclusion, this research tries to propose and develop a machine learning based framework for accurate and trustworthy non-invasive glucose monitoring by utilising the multi sensor data. This work addresses calibration and prediction challenges of diabetes management and could help to revolutionise the management facilities and improve the quality of life of millions of diabetes patients.

Thank you for your attention, and I look forward to your questions and feedback.

Reference list

Alghamdi, Y.A. *et al.* (2021) ‘The association of blood glucose levels and arterial stiffness (cardio-ankle vascular index) in patients with type 2 diabetes mellitus’, *Cureus* [Preprint]. doi:10.7759/cureus.20408.

An, Q. *et al.* (2023) ‘A comprehensive review on machine learning in healthcare industry: Classification, restrictions, opportunities and challenges’, *Sensors*, 23(9), p. 4178. doi:10.3390/s23094178.

Bhajane, K. *et al.* (2024) ‘Non-invasive blood glucose monitoring system’, *Journal of Physics: Conference Series*, 2763(1), p. 012017. doi:10.1088/1742-6596/2763/1/012017.

Bian, Q. *et al.* (2024) ‘A hybrid transformer-LSTM model apply to glucose prediction’, *PLOS ONE*, 19(9). doi:10.1371/journal.pone.0310084.

Ceriello, A. *et al.* (2022) ‘Glycaemic management in diabetes: Old and new approaches’, *The Lancet Diabetes & Endocrinology*, 10(1), pp. 75–84. doi:10.1016/s2213-8587(21)00245-x.

Clarke, W.L. (2005) ‘The original Clarke Error Grid Analysis (EGA)’, *Diabetes Technology & Therapeutics*, 7(5), pp. 776–779. doi:10.1089/dia.2005.7.776.

ElSayed, N.A. *et al.* (2023) ‘16. diabetes care in the hospital: *standards of care in diabetes—2024*’, *Diabetes Care*, 47(Supplement_1). doi:10.2337/dc24-s016.

ElSayed, N.A. *et al.* (2024) ‘Introduction and methodology: Standards of care in diabetes—2025’, *Diabetes Care*, 48(Supplement_1). doi:10.2337/dc25-sint.

Habehh, H. & Gohel, S. (2021) ‘Machine learning in Healthcare’, *Current Genomics*, 22(4), pp. 291–300. doi:10.2174/1389202922666210705124359.

Hussain, M. *et al.* (2024) ‘A comprehensive review on Deep Learning-based data fusion’, *IEEE Access*, 12, pp. 180093–180124. doi:10.1109/access.2024.3508271.

Jiang, H. & Ke, H. (2024) ‘Research progress in multi-sensor data fusion algorithms’, *Proceedings of the 2024 7th International Conference on Computer Information Science and Artificial Intelligence*, pp. 547–552. doi:10.1145/3703187.3703279.

Joshi, A.M. & Kor, P. (2024) ‘Smart glucometer for personalized health management of diabetes care’, *Proceedings of the 2024 6th International Conference on Software Engineering and Development*, pp. 73–81. doi:10.1145/3686614.3686623.

Klein, H.E. (2023) *Diabetes prevalence expected to double globally by 2050*, *AJMC*. Available at: https://www.ajmc.com/view/diabetes-prevalence-expected-to-double-globally-by-2050 [Accessed: 25 March 2025].

Min, S. *et al.* (2025) ‘Minimally and non-invasive glucose monitoring: The road toward commercialization’, *Sensors & Diagnostics* [Preprint]. doi:10.1039/d4sd00360h.

Moses, J.C. *et al.* (2024) ‘Non-invasive blood glucose monitoring technology in diabetes management: Review’, *mHealth*, 10, pp. 9–9. doi:10.21037/mhealth-23-9.

Nomura, A. *et al.* (2021) ‘Artificial Intelligence in current diabetes management and prediction’, *Current Diabetes Reports*, 21(12). doi:10.1007/s11892-021-01423-2.

Nyiramana, M.P. (2024) ‘Advances in non-invasive glucose monitoring: Challenges, technologies, and future prospects’, *Research Output Journal of Public Health and Medicine*, 3(3), pp. 1–5. doi:10.59298/rojphm/2024/3315.

Patel, V. & Shah, A.K. (2021) ‘Machine Learning for Biomedical Signal Processing’, *Machine Learning and the Internet of Medical Things in Healthcare*, pp. 47–66. doi:10.1016/b978-0-12-821229-5.00002-1.

Pfob, A., Lu, S.-C. & Sidey-Gibbons, C. (2022) ‘Machine learning in medicine: A practical introduction to techniques for data pre-processing, hyperparameter tuning, and model comparison’, *BMC Medical Research Methodology*, 22(1). doi:10.1186/s12874-022-01758-8.

Rahman, A. *et al.* (2024) ‘Machine learning and deep learning-based approach in Smart Healthcare: Recent advances, applications, challenges and opportunities’, *AIMS Public Health*, 11(1), pp. 58–109. doi:10.3934/publichealth.2024004.

Rajesh Hanni, J., Santhosh, K.V. & Srinidhi, N.N. (2024) ‘Design of a novel predictive technique to estimate liquid level and concentration using multi-sensor data fusion’, *IEEE Access*, 12, pp. 98787–98802. doi:10.1109/access.2024.3422610.

Rajkomar, A., Dean, J. & Kohane, I. (2019) ‘Machine learning in medicine’, *New England Journal of Medicine*, 380(14), pp. 1347–1358. doi:10.1056/nejmra1814259.

Rangayyan, R.M. & Krishnan, S. (2024) *Biomedical Signal Analysis*. Hoboken, NJ: Wiley-IEEE Press.

Rodbard, D. (2017) ‘Continuous Glucose Monitoring: A review of recent studies demonstrating improved glycemic outcomes’, *Diabetes Technology & Therapeutics*, 19(S3). doi:10.1089/dia.2017.0035.

Rodriguez-Calero, I.B. *et al.* (2020) ‘Prototyping strategies for stakeholder engagement during front-end design: Design practitioners’ approaches in the medical device industry’, *Design Studies*, 71, p. 100977. doi:10.1016/j.destud.2020.100977.

Roglic, G. (2016) *Global report on diabetes*. Geneva, Switzerland: World Health Organization.

Seaquist, E.R. *et al.* (2013) ‘Hypoglycemia and diabetes: A report of a workgroup of the American Diabetes Association and the endocrine society’, *Diabetes Care*, 36(5), pp. 1384–1395. doi:10.2337/dc12-2480.

Singh, A.K. & Berretti, S. (2024) *Data fusion techniques and applications for Smart Healthcare*. S.l.: Academic Press.

Sun, T., Liu, J. & Chen, C.J. (2024) ‘Calibration algorithms for continuous glucose monitoring systems based on interstitial fluid sensing’, *Biosensors and Bioelectronics*, 260, p. 116450. doi:10.1016/j.bios.2024.116450.

Uhl, S. *et al.* (2023) ‘Effectiveness of continuous glucose monitoring on metrics of glycemic control in type 2 diabetes mellitus: A systematic review and meta-analysis of randomized controlled trials’, *The Journal of Clinical Endocrinology & Metabolism*, 109(4), pp. 1119–1131. doi:10.1210/clinem/dgad652.

Villena Gonzales, W., Mobashsher, A. & Abbosh, A. (2019) ‘The progress of glucose monitoring—a review of invasive to minimally and non-invasive techniques, devices and sensors’, *Sensors*, 19(4), p. 800. doi:10.3390/s19040800.

Wiklund, M.E., Kendler, J. & Strochlic, A.Y. (2016) *Usability testing of Medical Devices*. Boca Raton: CRC Press.

World Health Organization (WHO) (2024) *Diabetes*, *World Health Organization*. Available at: https://www.who.int/news-room/fact-sheets/detail/diabetes#:~:text=The%20number%20of%20people%20living,for%20their%20diabetes%20in%202022. [Accessed: 24 March 2025].

Zamani, A.S. *et al.* (2024) ‘Implementation of machine learning techniques with big data and IOT to create effective prediction models for health informatics’, *Biomedical Signal Processing and Control*, 94, p. 106247. doi:10.1016/j.bspc.2024.106247.

Zanon, M. *et al.* (2013) ‘Non-invasive continuous glucose monitoring with multi-sensor systems: A Monte Carlo-based methodology for assessing calibration robustness’, *Sensors*, 13(6), pp. 7279–7295. doi:10.3390/s130607279.

Zhang, H. (2024) ‘Application of biosensors in non-invasive blood glucose monitoring’, *E3S Web of Conferences*, 553, p. 05001. doi:10.1051/e3sconf/202455305001.