Conceptual Review of Dual-Target Machine Learning Models for Prediction of Reproductive Health in Women

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Abstract: Infertility and menopause are two major interconnected challenges in women reproductive health. They are linked through ovarian ageing, endocrine changes and the progressive reduction in reproductive capacity, although infertility may also arise from causes unrelated to menopausal transition. This study is conceptually grounded in the application of dual-target machine learning models to improve the prediction of infertility risk and menopause transition. Most existing systems are single-target models that focus on predicting one outcome at a time. They predicted either infertility or menopause. This limits their ability to capture shared biological patterns and reduces the potential for integrated reproductive health analysis.

The dual-target machine learning approach addresses this gap by predicting infertility risk and menopause stage simultaneously from shared reproductive health data. This enables the model to learn common patterns associated with reproductive ageing and may improve predictive efficiency and clinical relevance.

The study highlights the importance of dual-target modelling in supporting early risk identification, improving clinical decision-making and enhancing more personalised reproductive healthcare. It is particularly relevant in resource-limited settings where delayed diagnosis and fragmented health data are common. It advances the development of integrated reproductive intelligent systems for improved women's health outcomes.

Keywords: *Infertility, Menopause, Single-Target Models, Dual-Target Models, Intelligent Systems*

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I. INTRODUCTION

Machine learning in healthcare is shifting from isolated, single-outcome prediction towards integrated biomedical intelligence. Traditionally, single-target models predict one clinical outcome at a time, based on a one-to-one relationship between input features and an output. This approach is simple and interpretable but does not fully reflect the biological reality that many health conditions are interconnected through shared mechanisms. Infertility and menopause are related, but distinct, reproductive health conditions. Infertility can result from multiple factors, while menopause marks the natural end of reproductive function due to ovarian ageing. Some of the variables associated with both outcomes include age, hormone levels, menstrual regularity and reproductive history (Orovou et al., 2025; Wu et al., 2025). Thus, modelling them entirely separately may fragment analysis of the reproductive life course.

Dual-target machine learning models address this limitation by predicting infertility risk and menopause transition simultaneously from a shared feature space. They treat the two outcomes as related rather than independent, allowing the model to examine how ovarian function and reproductive ageing evolve over time. Conceptually, this aligns with the broader movement in healthcare towards precision medicine and life-course modelling, in which multiple related conditions are analysed jointly rather than in isolation. This can

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provide clinicians with a more complete view of a patient's reproductive trajectory. It may support earlier identification of reproductive decline, improved fertility counselling and better management of the menopausal transition, which is especially valuable in Nigerian settings where reproductive health records are often incomplete or fragmented.

Recent studies support this integrated direction by showing the growing use of machine learning across reproductive health, including infertility prediction, embryo selection and hormonal monitoring (Grace et al., 2025; Linder et al., 2025; Rittenberg et al., 2025). A dual-target machine learning model treats infertility and menopause as interconnected domains that may benefit from shared data representations and multi-output learning (Macedonia, 2025; Kakkar et al., 2025). Related literature has similarly called for digital health systems that move beyond single-condition prediction towards holistic reproductive intelligence for women's health.

Dual-target models may strengthen knowledge representation because their two predictions draw on shared features. The model can capture latent relationships between infertility and menopause that single-target systems may miss. Shared representations may also make it easier to trace how specific variables affect both outcomes, particularly when combined with explainable AI. Therefore, the shift from single-target to dual-target modelling represents a more biologically coherent and clinically useful approach to representing women's reproductive health.

II. CONCEPTUAL VIEW OF SINGLE-TARGET MACHINE LEARNING MODELS

A single-target machine learning model is designed to predict one outcome at a time. It is generally easier to design, train, validate and interpret because all input variables are directed towards one defined output. Single-target models have made important contributions to infertility and reproductive research. Adekola et al. (2024) showed how stacked ensemble machine learning models could be used to predict infertility in women. Dehghan et al. (2025) reviewed machine learning techniques for predicting infertility treatment success and showed that machine learning can support assisted reproductive decision-making by identifying patterns in treatment data. Bereczki et al. (2025) demonstrated the importance of female preprocedural factors in predicting IVF outcomes, while Salih et al. (2025) showed that combining embryo images with patient clinical information can improve IVF prediction compared with relying on embryo images alone. AlSaad et al. (2025), Cohen et al. (2025), Mina et al. (2025), Ouyang and Wei (2025), and Zhang et al. (2025) also showed that AI has been widely explored in embryo grading, embryo selection and pregnancy outcome prediction.

Despite these benefits, single-target models have conceptual limitations. They often treat reproductive outcomes as isolated clinical problems rather than related phases of reproductive live of women. They may not fully capture the biological relationship among ovarian ageing, infertility and menopause transition. Separate models also typically require separate training, optimisation and validation pipelines, even when they use data from the same source. In low-resource settings such as Nigeria, this can increase data and implementation demands and may limit generalisability when sample sizes are small.

➢ *Architecture of a Single-Target Machine Learning Model*

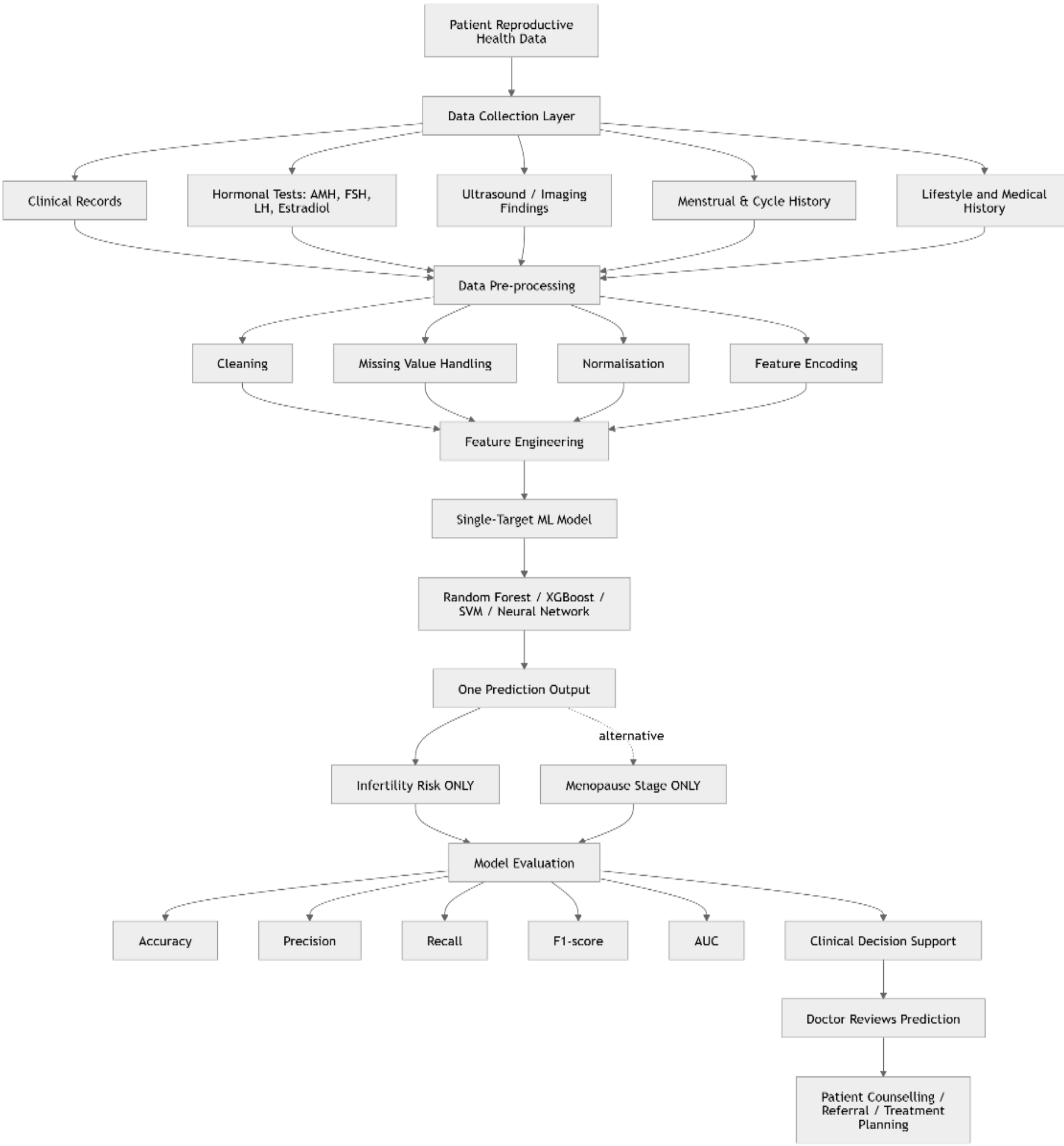

Fig 1. Conceptual Single-Target Reproductive Health Architecture

➢ *Conceptual View of Dual-Target Machine Learning Models*

A dual-target machine learning model is designed to predict two related outcomes from a shared set of inputs. It may be formulated as a multi-output or multi-task learning problem in which the model learns common representations from reproductive health data and then produces two outputs: infertility risk classification and menopause-stage prediction.

The conceptual strength of a dual-target model lies in shared learning. Infertility and menopause are not identical conditions, but they share related biological indicators, including age, ovarian reserve, menstrual irregularity, hormonal patterns, reproductive history and metabolic changes. A dual-target model learns from these shared variables and may use them to improve prediction for both infertility and menopause

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outcomes. Recent machine learning literature supports this logic. Abdelsamie et al. (2026) explained that multi-task learning can improve generalisation by sharing knowledge across related tasks. Tsai et al. (2025) showed that multi-task learning can predict multiple chronic diseases simultaneously by using patient records and disease relationships. Yoon et al. (2025) demonstrated that interpretable multi-task models supported the prediction of multiple clinical outcomes with practical advantages over separate single-outcome models.

A dual-target model uses a shared feature-representation layer and two prediction heads. The first output head classifies infertility risk as low, moderate or high. The second classifies menopause status as premenopause, perimenopause or postmenopause, or estimates the probability of transition. Candidate algorithms include Random Forest, XGBoost, Extra Trees, Convolutional Neural Networks, Support Vector Machines and transformer-based models. The choice of algorithm should reflect the data type: tree-based models are suitable for structured clinical data, CNNs for imaging data, and transformer-based models for text or sequential data. Explainable AI methods such as SHAP can be used to show which features contribute most strongly to each prediction.

- *Architecture of a Dual-Target Machine Learning Model*

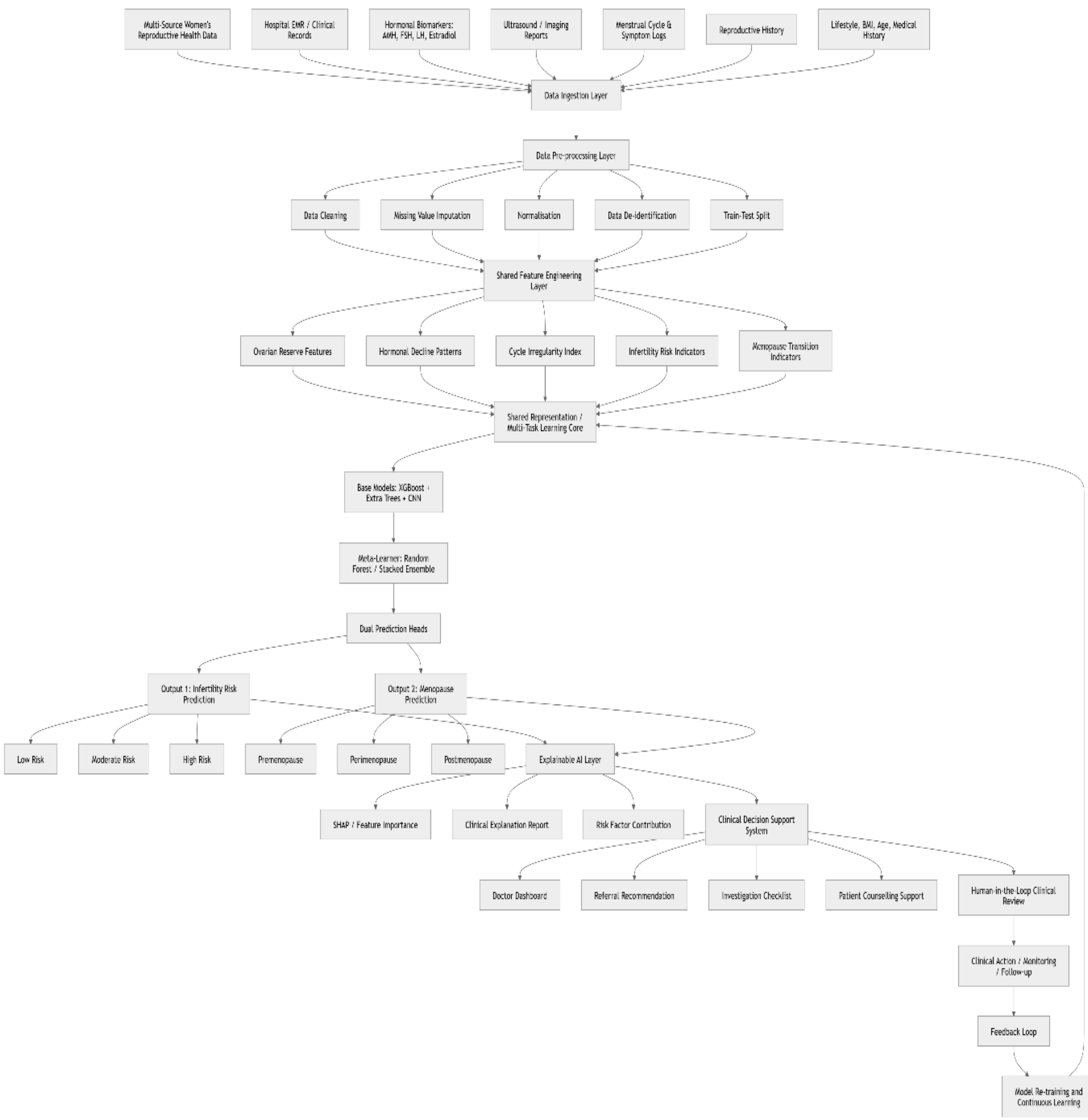

Fig 2. Conceptual Dual-Target Reproductive Intelligence Architecture

- *Gap Between Single-Target and Dual-Target Machine Learning Models*

The literature reveals a clear gap between single-target and dual-target machine learning models in reproductive health. Existing studies show strong progress in single-target prediction, especially for IVF success, embryo selection, live-birth prediction, early menopause prediction and postmenopausal risk prediction (Bereczki et al., 2025; Panjwani et al., 2025; Salih et al., 2025; Zhou et al., 2025). However, these models remain fragmented because they focus on isolated outcomes. Although infertility and menopause share some biological foundations in ovarian ageing and hormonal change, current machine learning studies rarely build models that jointly predict both conditions. Therefore, existing works did not fully address reproductive life-course needs of women. Another gap concerns contextual and population bias. Most reproductive AI models are trained on datasets from high-income settings, which may not represent the clinical, behavioural and social factors associated with infertility and menopause in Nigeria. Macedonia (2025), Grace et al. (2025), Linder et al. (2025), Mengistu et al. (2025), and Rittenberg et al. (2025) emphasised the importance of representative datasets, equity, ethical design and inclusive women's health innovation.

Another gap concerns explainability and clinical trust. Healthcare AI systems require transparency because human experts must understand why a model produces a prediction. Sounderajah et al. (2025) proposed STARD-AI to improve the report of diagnostic accuracy studies using AI while Alattal et al. (2025) and Moreno-Sánchez et al. (2026) emphasised explainability, human oversight, trustworthiness, privacy and accountability in medical AI. Hence, a dual-target reproductive model must not only be accurate but interpretable, clinically validated and safe for decision support. Many machine learning studies remain experimental, retrospective or single-centre, and few are embedded in hospital workflows, electronic medical records or patient-facing digital tools. This is particularly important in Nigeria, where a reproductive intelligence system must operate within real clinical constraints such as incomplete records, limited digital infrastructure and variable clinician workloads. Thus, the major literature gap is the absence of an integrated, dual-target, explainable and clinically deployable reproductive intelligence model that capable of predicting both infertility risk and menopause-related transition by exploring shared women reproductive health data.

- *Benefits of Dual-Target Prediction of Reproductive Health in women*

The model considers infertility and menopause as reproductive health issues common to women because ovarian reserve, menstrual patterns and hormonal balance may affect both fertility and menopausal transition. The model is capable of identifying combinations of hormonal profiles, menstrual irregularity and ovarian reserve indicators that suggest declining fertility or menopausal transition before a woman presents with clear symptoms. Dual-target modelling applies multi-task learning which reduces overfitting and allows related tasks to share representations. A dual-target reproductive intelligence system assists clinicians to answer two related questions: 'What is the infertility risk in women?' and 'What is her likely reproductive ageing or menopause-transition status?' These outputs supports counselling, referral, fertility-preservation discussions, lifestyle advice, hormonal evaluation and long-term monitoring. Women may experience infertility and menopause alongside emotional distress, uncertainty, stigma and limited access to reliable information. A patient-centred dual-target system supports a companion application that provides personalised risk awareness, symptom tracking and clinician-guided reproductive health education while the clinician remains responsible for final diagnosis and treatment decisions.

III. CONCLUSION

Conceptually, the proposed model advances the involvement of computer science in reproductive health by shifting machine learning from isolated reproductive prediction towards integrated reproductive life-course prediction. It applies multi-task learning to the reproductive health of women by treating infertility and menopause as related but distinct prediction targets. Also, it addresses the need for locally relevant AI systems that supports reproductive health doctors in Nigeria, where delayed diagnosis, stigma and fragmented care remain major challenges to early prediction of infertility and menopause transition.

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