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Methodology for a Dual-Target Reproductive Intelligence System for Early Prediction of Infertility and Menopause

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Abstract: Reproductive health of women involves complex, heterogeneous and interdependent clinical factors that make early risk assessment difficult through manual valuation alone. This study proposes a dual-target machine-learning reproductive intelligence system for predicting infertility risk and menopause transition from shared health data. The system integrates clinical records, hormonal profiles, laboratory results, ultrasound findings, menstrual history, age, body mass index, lifestyle factors, infection history and patient-reported symptoms.

It addresses a limitation in existing reproductive-health applications which commonly focus on isolated tasks, such as ovulation tracking, embryo grading, assisted-reproduction outcomes, symptom monitoring, without jointly modelling infertility and menopause across the reproductive life course. The proposed architecture uses a stacked ensemble of Extreme Gradient Boosting, Extra Trees and Convolutional Neural Networks as base learners. Their predictions are combined via a Random Forest meta-learner to classify women into infertility-risk categories and menopause-transition stages.

This design exploits complementary strengths in nonlinear feature learning, variable interaction detection and robust classification. SHAP additive explanations are incorporated to identify the contribution of each predictor and provide patient-level and global explanations. Thereby, improving transparency and clinical interpretability. The system is intended to support earlier screening, risk stratification, referral, and personalised reproductive-health decisions rather than replace professional diagnosis.

Its application is especially relevant in Nigeria and similar African settings where reproductive data remain underused and delayed assessment, repeated hospital visits, stigma, emotional distress and limited menopause services persist. The proposed methodology provides an integrated, explainable and context-sensitive foundation for intelligent decision support across the reproductive ageing continuum in women.

Keywords: *Machine learning, Infertility prediction, Menopause transition, Stacked Ensemble, Explainable Artificial Intelligence.*

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I. INTRODUCTION

This study presents a methodology for developing a dual-target intelligent system for the early prediction of infertility risk and menopause transition. These two medical challenges are complex biomedical prediction problems involving large, heterogeneous, and interrelated datasets. Infertility has diverse causes (World Health Organization, 2025), including ovarian disorders, hormonal imbalance, tubal factors, uterine abnormalities, endocrine dysfunction, lifestyle risks, age-

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related reproductive decline, and unexplained clinical conditions (Choudhary et al., 2025; Furqan et al., 2026; Raperport et al., 2026). Similarly, menopause is not merely the end of menstruation but a progressive biological transition marked by declining ovarian hormone production, reduced reproductive capacity, and vasomotor symptoms such as hot flushes and night sweats. Also, it may involve psychological changes, such as anxiety, depressive symptoms, metabolic alterations and increased cardiovascular vulnerability (Gibson et al., 2025; Kim et al., 2025; Shufelt, 2026). These conditions generate complex data patterns that may be difficult to interpret through manual clinical assessment alone. Machine learning, a branch of Artificial Intelligence (AI), supports these biomedical prediction tasks by identifying patterns across infertility and menopause-related variables.

Machine learning is a subfield of AI that enables computer systems to learn patterns from data, improve task performance, and make predictions without being explicitly programmed for every rule or decision (Razzaq & Shah, 2025; Garcia Quevedo & Kuri, 2026; Raţiu & Pop, 2026). Its algorithms can be trained on clinical records, laboratory results, hormonal profiles, ultrasound findings, menstrual-cycle history, age, body mass index, lifestyle variables, infection history and patient-reported symptoms to predict infertility- and menopause-related outcomes. Recent studies show that machine-learning models are increasingly used in assisted reproductive technology, infertility treatment, embryo assessment, ovarian stimulation planning, and clinical decision support (Dehghan et al., 2025; Kakkar et al., 2025). These applications suggest that computer-based prediction can support decision-making when traditional methods are slow, subjective, or inconsistent. Existing intelligent systems serve as decision-support tools in reproductive medicine, but their scope is limited. Many focus on fertility tracking, ovulation prediction, embryo grading, or IVF success prediction. These tools do not address the broader continuum of women's reproductive health; they often address infertility alone and rarely connect infertility prediction with menopause forecasting (Mengistu et al., 2025). Recent AI studies on menopause focus on postmenopausal risk prediction, symptom monitoring, cardiovascular risk, osteoporosis screening, and personalised care, but they do not integrate infertility risk and menopause prediction in one model (Panjwani et al., 2025). This indicates a research and system-design gap in reproductive health.

This study therefore proposes a methodology for developing a dual-target machine-learning reproductive intelligence system for infertility and menopause. A dual-target system predicts more than one related outcome from shared reproductive health data. The system will estimate infertility risk and identify menopause-transition patterns. A stacked ensemble comprising Extreme Gradient Boosting (XGBoost), Extra Trees, and Convolutional Neural Networks (CNNs) as base learners will be trained to classify women into infertility-risk levels and menopause stages. A Random Forest meta-learner will combine the base-model outputs to produce the final predictions. SHAP will be used to explain how individual variables influence each prediction. This approach is particularly relevant to Nigeria and other African healthcare settings, where women's reproductive health data are often underused. Many women experience delayed infertility diagnosis, prolonged hospital visits, social stigma, emotional distress, and limited access to menopause care.

II. METHODOLOGICAL FOUNDATION OF MACHINE LEARNING IN REPRODUCTIVE HEALTH

Machine learning provides computational methods that can learn complex patterns from clinical data and generate predictive outputs for diagnosis, prognosis, and decision support. This provides a useful methodological foundation for representing two complex biomedical conditions that generate heterogeneous clinical data. Infertility and menopause fit this methodology because both involve hormonal assays, imaging results, reproductive history, menstrual patterns, lifestyle variables and patient-reported symptoms. The methodological relevance of machine learning therefore depends on its ability to integrate these heterogeneous variables and identify relationships that may be difficult for clinicians to interpret manually, especially where patient records are fragmented and specialist access is limited (Alhumaidi et al., 2025; Dai, 2025; Raţiu & Pop, 2026).

Recent literature shows that machine learning has been applied in infertility diagnosis, IVF outcome prediction, embryo assessment, ovarian stimulation planning, pregnancy prediction, and clinical decision support (AlSaad et al., 2025; Findikli et al., 2025; Wu et al., 2025). Similarly, artificial intelligence is increasingly being explored in menopause and postmenopausal health through early-menopause prediction, symptom monitoring, cardiovascular risk assessment, cognitive-decline detection, and personalised care (Ang, 2025; Miao et al., 2025; Panjwani et al., 2025; Zhou et al., 2025). These studies confirm the methodological potential of machine learning in women's reproductive health. However, most existing models are single-target systems that predict one outcome at a time. This creates a methodological gap because infertility and menopause are biologically connected through ovarian ageing, hormonal decline and reproductive capacity but are commonly modelled as separate computational problems.

- *Conceptual Methodology of Single-Target Machine-Learning Models*

A single-target machine-learning model is designed to predict one clinical outcome from a set of input variables. Methodologically, such a model follows a one-input-to-one-output structure in which clinical features are collected, cleaned, transformed, and passed into a classifier or regression model to produce one prediction. The strength of single-target methodology is its simplicity. It is easier to formulate the research objective, define the dependent variable, select predictors, train the algorithm, and evaluate model performance (Hanassab et al., 2025; Salih et al., 2025). However, single-target models have methodological limitations. They treat

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reproductive health problems as isolated outcomes. A model trained only to predict infertility ignores menopause-related indicators, while a model trained only to predict menopause ignores infertility-related indicators. Also, single-target models may require separate datasets, preprocessing pipelines and validation processes for each reproductive outcome (Agirsoy & Oehlschlaeger, 2026). They fail to exploit shared biological features between infertility and menopause. They may be less efficient in low-resource settings where large, complete reproductive datasets are not readily available.

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

A dual-target machine-learning model is designed to predict two related outcomes from shared input data. This study presents two prediction targets: infertility risk and menopause-transition stage. Methodologically, the task can be framed as a multi-output classification or multi-task learning problem. Instead of developing two completely separate models, one system learns shared representations from women's reproductive health data and generates two prediction outputs. The first output predicts infertility risk, while the second predicts menopause stage or transition probability. The methodological justification for a dual-target model is grounded in multi-task learning, which can improve model generalisation by allowing related prediction tasks to share representations during training (Abdelsamie et al., 2026; Tsai et al., 2025; Yoon et al., 2025).

This approach is useful when two or more clinical outcomes share common risk factors or biological pathways. Infertility and menopause are appropriate for dual-target modelling because both are associated with age, ovarian reserve, menstrual irregularity, hormonal profile, body mass index, reproductive history, lifestyle factors, and endocrine changes. A dual-target model can therefore learn common reproductive-health patterns and use them to support both infertility and menopause prediction.

This methodology differs from single-target modelling in structure and clinical purpose. A single-target model learns only one outcome, whereas a dual-target model learns a shared reproductive representation and then separates into two prediction outputs. One output produces infertility-risk classification, while the other produces menopause-stage classification. This makes the model more suitable for reproductive intelligence because it treats women's reproductive health as a life-course continuum rather than as separate disease episodes.

- *Data Methodology for a Dual-Target Reproductive Intelligence Model*

The first methodological stage in developing a dual-target model is data collection. The proposed system requires multi-source reproductive health data, including hospital electronic medical records, laboratory results, hormonal biomarkers, ultrasound findings, menstrual-cycle history, reproductive history, lifestyle factors, infection history, and patient-reported symptoms. Relevant variables may include menstrual irregularity, vasomotor symptoms, sleep disturbance, mood changes, hot flushes, night sweats, cycle-length variation, hormonal profiles, and reproductive-ageing indicators. This data design is important because infertility and menopause cannot be predicted accurately from one variable alone. The literature on reproductive AI increasingly supports the use of multimodal and real-world clinical data because reproductive outcomes are influenced by clinical, biological, imaging, and behavioural variables (Alhumaidi et al., 2025; Macedonia, 2025; Ouyang & Wei, 2025). Locally collected data are particularly important because models trained only on Western populations may not generalise to African clinical settings.

- *Data Preprocessing and Feature-Engineering Methodology*

The second methodological stage is data preprocessing. Reproductive health datasets often contain missing values, inconsistent coding, incomplete laboratory results, and differences in clinical documentation. Preprocessing should therefore include data cleaning, duplicate removal, missing-value imputation, outlier detection, normalisation, categorical encoding, and patient-level splitting into training, validation, and test sets. Where class imbalance exists, stratified sampling or appropriate resampling techniques may be required. Feature engineering is central to the success of the dual-target model. Raw reproductive data may be transformed into clinically meaningful variables such as ovarian-reserve indicators, hormonal-decline patterns, cycle-irregularity indices, menopause-symptom burden, reproductive-ageing signals, and lifestyle-risk scores. Derived features should use only information available at the intended prediction time to avoid target leakage (Bereczki et al., 2025; Miao et al., 2025; Zhou et al., 2025).

- *Model-Development Methodology*

The proposed dual-target model will use a stacked ensemble architecture. XGBoost and Extra Trees will serve as base learners for structured clinical and laboratory data while CNNs will be used when raw ultrasound images are available. If the dataset contains ultrasound reports rather than images, structured report features or text-processing methods should be used instead. The base learners will generate probability estimates for each target through out-of-fold training. Random Forest algorithm will be used as a meta-learner to combine the outputs from the base learner to produce final predictions. XGBoost is suitable for structured clinical and laboratory data because of its predictive strength in tabular datasets. Extra Trees may improve robustness by reducing variance through randomised tree construction. The stacked ensemble is appropriate because reproductive-health data are heterogeneous, and a single algorithm may not capture the relationships among hormonal, clinical, imaging, and symptom-based variables. Ensemble learning may improve model stability by combining the strengths of multiple algorithms. Recent reproductive-AI studies support combining imaging, clinical, and laboratory variables to improve prediction in infertility and assisted reproductive technology contexts (Fu et al., 2026; Li et al., 2026; Masip et al., 2026).

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The methodological contribution of the present study lies in extending this ensemble logic beyond IVF or embryo prediction to a dual-target reproductive intelligence system for infertility and menopause.

- *Dual-Target Output Design*

The dual-target model should produce two outputs. The first is infertility-risk prediction, which classifies women into low-, moderate-, and high-risk categories. The second is menopause-stage prediction, which classifies women as premenopausal, perimenopausal, or postmenopausal, or estimates the probability of transition within a defined time horizon. This two-output design is methodologically stronger than a single-output model because it allows one system to support two related clinical decisions.

The dual-output structure may also improve clinical interpretation. A woman may have moderate infertility risk and an elevated probability of early perimenopause. This suggests a need for timely reproductive counselling. Another woman may have high infertility risk but a low probability of menopause transition, suggesting that other causes, such as tubal factors, endocrine imbalance, or uterine abnormalities, should be prioritised. Dual-target prediction may therefore support more personalised clinical reasoning than a single-target model.

- *Model-Evaluation and Validation Methodology*

Model evaluation should be performed separately for each target and jointly for the dual-target system. For each target, evaluation should include accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC), confusion matrices, and calibration measures. Additional multi-output measures may include macro-averaged F1-score, weighted F1-score, Hamming loss, subset accuracy, calibration error, and per-target AUC. Internal validation should use cross-validation or a held-out patient-level test set. External validation is also important because models developed on one hospital dataset may perform poorly in another hospital because of differences in patient populations, laboratory practices, and clinical documentation. Recent AI reporting guidelines emphasise transparent dataset description, validation strategy, bias assessment, performance reporting, and clinical applicability (Sounderajah et al., 2025). The model should therefore be validated internally and externally across different healthcare facilities, with subgroup performance reported where feasible.

III. EXPLAINABILITY AND CLINICAL DECISION-SUPPORT METHODOLOGY

Explainability is essential in reproductive healthcare because clinicians and patients need to understand the basis of AI predictions. The proposed model will use SHAP to explain how variables such as age, anti-Müllerian hormone (AMH), follicle-stimulating hormone (FSH), menstrual irregularity, body mass index (BMI), reproductive history, and vasomotor symptoms contribute to infertility and menopause predictions. Explainable AI supports clinical trust, improves transparency, and reduces the risk of black-box decision-making (Alattal et al., 2025; Hanassab et al., 2025; Moreno-Sánchez et al., 2026). The dual-target model should be integrated into a clinical decision-support system rather than used as an autonomous diagnostic tool. The system should generate risk scores, feature explanations, investigation checklists, referral recommendations, and counselling prompts. The clinician remains responsible for final diagnosis and treatment decisions.

This human-in-the-loop methodology is important because infertility and menopause involve medical, emotional, cultural and ethical issues that cannot be delegated fully to an algorithm. Recent healthcare-AI literature supports lifecycle management, human oversight, transparency, safety, fairness and continuous monitoring for AI-enabled medical systems (Food and Drug Administration, 2025; World Health Organization, 2026).

IV. IMPORTANCE AND SIGNIFICANCE OF THE DUAL-TARGET MODEL IN HEALTHCARE

The dual-target model is significant because it moves reproductive healthcare from fragmented prediction towards integrated reproductive intelligence. First, it supports early detection. Women may present with symptoms that suggest both fertility decline and menopausal transition, and a dual-target system can identify overlapping signals within one assessment. Second, it may improve data efficiency by allowing related tasks to share information, which is relevant where reproductive-health data are limited or underused. Third, it may improve clinical efficiency because one system can support infertility-risk classification and menopause-transition prediction at the same time, reducing repeated assessments and supporting faster referral decisions. It also promotes patient-centred care by supporting counselling, reproductive planning, fertility-preservation discussions, menopause education, and long-term follow-up. Finally, the model has local relevance because it is intended to be trained on Nigerian reproductive-health data, making predictions more sensitive to local clinical realities, disease patterns, and health-seeking behaviours.

V. RECOMMENDATIONS

A dual-target machine-learning model in healthcare should be designed with multi-output methods that enable the simultaneous prediction of related clinical outcomes from shared patient data. Heterogeneous data sources, such as electronic health records, laboratory results, imaging and patient-reported symptoms should be integrated through a unified preprocessing pipeline. Ensemble-learning techniques may be used to improve predictive performance while explainable-AI methods should be integrated to support interpretability. Also, the methodology should include patient-level data splitting, calibration assessment, external validation, subgroup evaluation, privacy safeguards and continuing clinical oversight. This approach strengthens clinical decision support, reduce data redundancy and support holistic patient care.

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VI. CONCLUSION

This research addresses the methodological gap created by the absence of a locally relevant, explainable, dual-target machine-learning model that jointly predicts infertility risk and menopause transition. It advances the application of computer science in reproductive health by proposing a stacked-ensemble, dual-target model for the early prediction of infertility risk and the management of menopause transition. The proposed system supports early detection, improved clinical decision-making, personalised counselling and reproductive life-course management. Also, it contributes to African digital health by proposing a system that learns from local clinical data and addresses reproductive-health challenges in Nigeria, where infertility diagnosis and menopause care remain fragmented.

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