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REVIEW OF FECUNDITY PREDICTION MODELS WITH RESPECT TO FERTILITY AND SUBFERTILITY MODELLING

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ABSTRACT
Couples understanding their respective fecundity gives the opportunity for keeping track of their fertility status and thus helps to know if and when medical intervention is needed or not. To help understand couples fecundity, fecundity prediction models were developed using statistical/machine/deep learning models. Fecundity prediction models are developed with the possible need for improvements or advancements, and to identify the improvements and advancements with respect to analyzing fecundity heterogeneities among fertile and sub fertile couples, the models from 2000 to 2025 are reviewed. In reviewing existing models for fecundity studies, the models were further categorized from the existing categories, and each fecundity models category were reviewed against the fertility and subfertility definitions (which are applicable to fertile and subfertile couples respectively). Based on the review outcome, it was observed that assumptions used for developing most models for analyzing subfertility heterogeneities in each models category may deny the models from achieving satisfactory conclusive analysis on fecundity heterogeneities among couples. Also, existing models does not explicitly distinguish fertility and subfertility during fecundity analysis.

Keywords: Fecundity, Fecundity prediction model, Subfertility, Statistical learning, Deep learning

INTRODUCTION
Capabilities of achieving pregnancy is referred to as fecundity and the process of determining pregnancy capabilities is known as fecundity prediction (Wang et al. 2022). Fecundity could be attributed to any living being that can reproduce, like humans, animals or plant. However, the focus of this study is human, specifically women. Forecasting fecundity needs examining the biological and reproductive variability associated with women achieving pregnancy. The understanding can assist in assessing a woman's fertility status early, facilitating prompt awareness and potential treatment of infertility if identified (Muhammad et al., 2025; Muhammad et al., 2023).
Traditionally, predicting fecundity has relied on interactions between couples and specialists, such as gynecologists and obstetricians. However, irrespective of the fact that specialists for every health care services (including fecundity analysis) are available and effective services are rendered to the respective seekers, time taken for rendering services to seekers is high especially when population of seekers is high, the services are expensive (Mbungeet al., 2022), possible bias services rendered (Ricks et al., 2022). However, data of well managed seekers for health care could be collected and analyzed using data mining techniques so as to support the rendering of heath care services to seekers.
Although, pregnancy care involves rendering health care services to women before, during and after pregnancy but, the pregnancy care period considered in this research is before pregnancy and the health care service is women fecundity prediction. To carry out the task of fecundity prediction, women are observed based on factors like intercourse, fertility (men and women), women menstrual cycles and environmental factors like contraceptive usage. Therefore, any supporting techniques that must be developed for fecundity prediction must also consider these factors.
The traditional approach used for fecundity prediction involves interactions with specialists. Based on the specialist's memory-based self-report, the prediction results cannot be assessed and thus allowing the specialist to sometime be bias during diagnosis (Rickset al., 2022). Based on the setback encountered by the traditional approach, fecundity prediction models were developed using data mining techniques to improve (in terms of results assessment and efficiency) the process of carrying out fecundity prediction task. Depending on the context under consideration, Pregnancy prediction, Fecundity, Conception probability, Fertility awareness are all terms used to describe the measurement of capability of couples reproduction, therefore, this study used any of the mentioned concepts to describe the task under review depending on the context under consideration.

Fecundity Prediction Using Machine Learning
Machine learning (ML) involves the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data (Malik et al., 2020; Shehu et al., 2018). ML can be applied to various health care domains like pregnancy complications care (Dewanet al., 2023), Pregnancy prediction (Muhammad et al., 2025; Muhammad et al., 2023). The general ML approaches for solving data mining problems are Association, Classification and Clustering (Aguiar-Pérezet al., 2023). Association approach deals with the discovery of frequently occurred attribute value in datasets, Classification approach deals with the generation of rules in identifying class of data in a dataset base on the dataset attributes. Clustering deals with categorizing a dataset into clusters, where data within the clusters are very similar while data between the clusters are less or not similar.
Bayesian, Regression, Long Short Term Memory and Descriptive statistical methods are the major data mining methods used in the development of fecundity prediction models. Several research contributions developed fecundity prediction models to answer problems like timing intercourse for optimal fecundity (Scarpa and Dunson, 2007), Menstrual Cycle Length (MCL) roles during fecundity (Yuet al., 2022), the effect of environmental chemicals to MCL roles during fecundity (Kim et al. 2019), ovulation timing (Fantonet al.,

2022), predicting pregnancy of larger population (Muhammad et al., 2023; Liu et al., 2019).
Machine/Deep/Statistical models developed by previous researches to analyze fecundity data were grouped into three (3) categories; Time to pregnancy models (TTP), Barrett-Marshall and Schwartz models (BMS) and Extended time to pregnancy (ETTP) (Echocard, 2006). Although, this study also groups the models into three; TTPs, BMS and Deep learning for pregnancy prediction (DLPP), where the TTP and ETTP are categorized as TTPs. The grouping are based on how previous researches models characterized the biological and sexual behavior heterogeneity with respect to fecundity studies.
However, results achieve during fecundity analysis also depends on four (4) categories of fertility: Fertility; Capabilities to conceive without medical intervention within a cycle, Subfertility; capability to conceiving without medical intervention but with longer time (more than one cycle) to conceive after trying, Infertility; Incapability to conceive without medical intervention and Sterility; Incapability to conceive with or without medical intervention. Hence, fecundity prediction models developed by existing researches are applicable to any of the fertility category. However, reviews on existing fecundity prediction models based on how the models analyzes the fertility categories are yet to be carried out. Therefore, this study focuses on reviewing existing fecundity prediction models analysis with respect to the fertility and subfertility categories. This will help future studies to focus on the fertility category (between fertility and subfertility) with weaker analytical resolutions on the heterogeneities in fecundity studies.
In this study's literature review, existing works related to fecundity analytics are categorized based on Muhammad et al. (2023) and Liu et al. (2019) categorization of fecundity analytics, and then each category is reviewed. Based on Muhammad et al. (2023) and Liu et al. (2019) categorization of fecundity analytics, they are categorized as TTPs, BMS, and DLPP.

Review of Statistical/Machine/Deep Learning Models for Fecundity Analysis

Table 1 describes the placement of every research contribution in a taxonomy of statistical/machine/deep learning model for fecundity analysis based on how this study's focused fertility categories wereanalyzed. For more specifics, fertility category is the capability to carry out the process of achieving pregnancy and achieve it within a cycle without any medical intervention, while Subfertility category is the capability to achieve pregnancy after trying within a period of two (2) to twelve (12) cycles without medical intervention or intend pregnancy delay. This study strictly used this fertility categories descriptions to review every identified existing fecundity analytic model for fecundity analysis.

Table 1: Taxonomy for Fecundity Analysis Models Based on Fertile and sub Fertile Couples

Models and Fertility Categories	Major Contributions	Authors
TTPs Models		
Fertility	i. Generalized distributive effect of fecundity covariates on probability of conception within a cycle. ii. Menstrual cycle fertile window detection model using cervical mucus marker. iii. Menstrual cycle fertile window detection considering unexplained heterogeneity of covariate effect on probability of pregnancy. iv. Modelling age heterogeneity effect on conception.	i. Ecochard and Clayton (2000) ii. Dunson and Colombo (2003) iii. Pennoniet al. (2017) iv. McDonald et al. (2011)
Subfertility	Assumes proposed TTPs models are also applicable to subfertile couples since the model are distributions extracted from both fertile and subfertile couples details	
BMS Models		
Fertility	i. Modelling daily effects of dependent or independent intercourse heterogeneity as covariate on probability of pregnancy within a cycle. ii. Improved modelling of day specific probability of pregnancy within a cycle with respect to the selective power of categorical predictors' levels. iii. Flexible Characterization of day specific probability of pregnancy within a cycle. iv. Modelling mucus covariate effect on day specific probability of conception within a cycle. v. Distributive effects of covariates on pregnancy probability within a cycle.	i. Dunson (2001), Kim et al. (2010) ii. Dunson and Stanford (2005) iii. Kim et al. (2012) iv. Colombo et al. (2006) v. Lumet al. (2016), Lumet al. (2017); Kim et al. (2019)
Subfertility	Assumes probability of pregnancy within current cycle is constant over all cycle with similar fecundity details. Therefore, all proposed BMS models are applicable to subfertile couples.	
DLPP		
Fertility	i. Scalable modelling of intercourse heterogeneity effect on pregnancy probability within a cycle. ii. Scalable modelling of the influence of various fecundity determinant factors of fecundity	i. Liu et al. (2019) ii. Naseem et al. (2023), Yland et al. (2022) and Zhan et al. (2022).
Subfertility:	Scalable modelling of intercourse heterogeneity effect on pregnancy probability within 7 cycles.	Liu et al. (2019), Muhammad et al. (2023)

Category 1 (TTPs)

In this review the TTPs models category was a combination of TTP and ETTP categories. The combination was due to the usage of similar statistical assumptions to develop fecundity models by both TTP and ETTP categories. The ETTP extension of TTP was due to an inclusion of assumption of fertilization process in fecundity to the existing TTP models (Ecochard 2006). However, during review of research contributions, TTP models was differentiated from the ETTP models.

The TTPs models focuses on analyzing fecundity based on the assumption that conception probability μ of any couple is determined within a menstrual cycle, and μ varies from couple to couple. Menstrual cycles M are assumed to be set of Bernoulli trials that results to either 1 (success in conception; if conception occurs in Mi where i = {1, 2, 3, …., n}) or 0 (failure in conception; if conception does not occur in Mi). This implies that μ is determined as described in equation 1.

$\mu = \text{Bernoulli}(M_i)$ (1)

TTPs Analysis on Fertility Category

Based on the fact that fecundity of fertility categorized couples (also known as, fertile couples) are within a menstrual cycle, it can be assumed that the discoveries on the fecundity of fertile couples should be from within a menstrual cycle. TTPs models used this assumption and proposed different statistical distributions for determining μ and its influencers.

Earlier TTP models proposed geometric distributions for analyzing fecundity of fertile couples based on an assumption that fecundity behavior over different menstrual cycles are homogenous (see equation 2) (Ecochard 2006), but recent TTP models used more practical assumption that fecundity behavior is heterogynous to proposed a more flexible distributions.

$\mu = \mu_i, \forall i, i = 1, 2, 3, \dots, N$ (2)

Ecochard and Clayton (2000) proposed a TTP multivariate parametric model based on the foundation of Hougaard (1986) model. A generalization of the three-parameter family distributions was proposed to model fecundity at couple levels considering fixed and random effect of fecundity covariate. Equation 3 describes Ecochard and Clayton (2000) model.

$\exp(\mu_i) \sim P(\alpha, \delta, \theta)$ (3)

The three-parameter family distributions are the non-negative stable distribution (when θ = 0), the gamma distribution (when α = 0), inverse Gaussian distribution (when α = 1/2). The significant features of the three-parametric family distributions are; 1) The outcome is closed under the selection induced by pregnancy and 2) The distribution leads to close-form expression for likelihood terms.

Dunson and Colombo (2003) focused on modelling fertility period (with respect to cervical mucus) as influencing factor for estimating conception probability. The work established a Bayesian model for detecting most fertile day for conception based on the cervical mucus marker. They observed conception probability μ based on cervical mucus baseline trajectory α as equation 4, this corresponds to Harville and Mee, (1984) generalized probit mixed model for the original polytomous mucus score.

$\mu_{ij}(s) = \alpha(s) + g\{s; \alpha(s)\}(\Gamma x_{ij} + \Lambda_1\eta_{i1} + \Lambda_2\eta_{ij2})$ for $s \in [s_1, s_M]$ (4)

where α(s) is the expectation of $\mu_{ij}(s)$ across the women i and cycle j, s denotes day related to mucus hydration peak, x_{ij} represent a covariate vector of i and j. Γ is an unknown regression constant, η_{i1} and η_{ij2} represents latent variables measuring deviations from women and cycles respectively (η_{i1} from trajectory in the mucus hydration score, while η_{ij2} from trajectory for woman i). Λ_1 and Λ_2 are square matrices of loading factors for identifiability purpose. g{s; α(s)} is a 1 x l vector containing known smooth functions of s and α(s). The advantage of equation 4, is that the curve it generates accommodates deviations with respect to the overall level of fertility, when compared to some models like Barry (1995) model that generates curve that accommodates subject and time-specific deviations. The proposed Bayesian model for the baseline trajectory mucus hydration score α determination is given as equation 5 (for prior distribution) and Monte Carlo Macov Chain (MCMC) algorithm (for posterior evaluation). See Dunson and Colombo (2003).

$\alpha(s_M) \sim N(\mu_{\alpha M}, \sigma^2_{\alpha M})$ (5)

Motivated with the fact that pregnancy probability cannot be explicitly explained only with respect to observed covariates but also with unexplained heterogeneity, Pennoniet al., (2017) proposed an ETTP model to determine fertile window. Probability of conception Uwas assumed to exhibits a first-order Markov Chain with two state process (1; successful in conception, 0; unsuccessful in conception), of which the unexplained heterogeneity was accounted for in the proposed model as any response variable Y(t) (where t = 1,….., T; fertile window) which depends on U(t). Assuming Y(t) are conditional independent in U, then the conditional response probabilities are parameterized as in equation 6, where a Bernoulli distribution was assumed for the response variable with a certain success probability.

$P(t)_{y|ux} = \mu_y + \alpha_u + x_{1it}\beta$ (6)

where$P(t)_{y|ux}$ represents the fertility window measurements, μ_y is the cut-point coefficient related to the response variable when equal to 1. α_u represents latent process support point when it is equal to the first latent state. The α_u parameter helps determines how the probability varies according to the two states of the chain. β is the vector of the regression coefficients for the observed covariates in x. β also helps in measurement of the influence of each covariate on the conception probability.

McDonald et al. (2011) generated an ETTP logistic-normal-geometric model (as described in equation 7) for modelling the effect of age, net of the coital pattern to fecundity. The model was differentiated from the existing models (Dunson et al., 2002; Dunson et al., 2004) for estimating age effect to fecundity, using the fact that total dependence of conception probability on coital pattern while estimating the age effects on conception probability is a limitation to their proposed model. McDonald et al. (2011) modelled the effect of age to the probability of conception for childless women while controlling coital pattern within a menstrual cycle.

$\text{logit}(\text{fecundity}) = s(\text{age}) + XIY + Z\sigma$ (7)

wheres(age) is modelled using restricted cubic splined with knots at ages 24, 28 and 32. This due to the scope of the proposed model. X, Y and Zσ represents other covariates, regression effects and random effects of unobserved heterogeneity in the risk of conception.

TTPs Limitations in Analyzing Fertility Category

Although, TTP models category analyzes heterogeneity of fecundity within menstrual cycles across couples, be it fecundity with respect to fertilization pattern or fecundity with respect to fertilization and fecundity covariates, but the TTPs pays less interests on modelling couples daily details pattern within a menstrual cycle like heterogeneity of effect of intercourse within fertile window to pregnancy probability. By this, it is presumed that the analysis results of the TTP models are probabilistic estimations of fertile couple fecundity with respect to how it can be influenced by its covariates. TTP less consideration of coital pattern information during developing its models serve as limitation

to its model and thus enabling recent research contributions to use the ETTP models development assumption.
While the ETTP models category improves their analysis of fecundity heterogeneity by incorporating an assumption of fertilization; only coital occurrence on fertile window could result to pregnancy. The assumption was coiled out as a pragmatic approximation of the BMS assumption.

TTPs Analysis on Subfertility Category
TTPs are designed to analyze fecundity heterogeneity across couples (that is at couples level) (Ecochard 2006). This implies that any pregnancy probability estimation given by a TTPs model was based on the couple's fecundity level. TTPs analysis is assumed to be applicable to fertile or subfertile couples in as far as the couple's entries (based on the respective TTPs model parameters) are inputted.

TTPs Limitations in Analyzing Subfertilitycategory (Sub fertile Couples' Data)
Based on the fecundity description of subfertility, number of menstrual cycles needed to achieve pregnancy differentiates subfertile couples from fertile couples (Liu et al. 2019). An assumption of number of menstrual cycles was observed not to be included in the TTPs models.

Category 2 (BMS)
Modelling pregnancy capability using this approach gives opportunity for detail characterization of daily activities within a menstrual cycle. This approach assumes that every act of intercourse within a menstrual cycle independently affect the probability of conception p. This in turn means, a cycle outcome of pregnancy (success or not) is independent on another cycle pregnancy outcome.

BMS Analysis of Fertility Category
Using the assumption of intercourse occurrence contribution to achieving pregnancy within a cycle, Barratt and Marshall (1969) (Barrett-Marshall) introduced the method for modelling pregnancy prediction process as given below

$$P = 1 - \prod_d (1 - p_d)^{S_d} \quad (8)$$

Equation 8 can also be seen as a derivation from a Bernoulli random variable with parameter of probability of success pregnancy depending on days and number of intercourse occurrence. d represents a day in a menstrual cycle, pd estimates the probability of conception caused by intercourse occurring on d and sd is an indicator that describes whether intercourse occurred on d (if so, sd = 1) or not (or sd = 0). Barett-Marshall model as described in equation 2.8 was generated from equation 9, which assumes that, the capability for a woman to conceive depends on three (3) process; Ovule production o, Ovule fertilization f and Conceptus staying alive for at least six (6) weeks a (Colombo and Masaratto, 2000). And by statistics, the probability of successful conception can be determined by taking the product of the probabilities of the processes (as given in equation 9).

$$\text{fecundity} = Po.\ Pf\ .\ Pa \quad (9)$$

The product of Po and Pa is taken as the cycle viability (that is, the ability of the cycle to achieve pregnancy), which depends on influential factors (biological or chemical) deduced from the body chemistry (like BBT, cervical mucus, age) and activities (like chemical intake, exercise) of the couples. Barett-Marshall model assumed the cycle viability to be in a successful state (that is Po .Pa = 1), therefore focusing on only the probability of the ovule to be fertilized Pf. Ovule fertilization depends on the occurrence of intercourse, therefore, Pf generation depends on intercourse occurrence i and the day within the fertile period of a menstrual cycle d. Including the assumption that every episode of intercourse has independent effect on the probability of pregnancy, Barrett-Marshall model also assumed that the probability of pregnancy following intercourse on day d, say Pfd is constant between cycles and couples.
However, Schwartz et al. (1980) observed the need of including the cycle viability estimation to the Barrett-Marshal model, so as to improve the limitation of Barrett-Marshal model. By this Schwartz et al. (1980) model is given as in equation 10. Where K is the probability of cycle viability. Equation 10 is known as the foundation BMS for improved proposed pregnancy probability models.

$$P = K\{1 - \prod_d (1 - p_d)^{S_d}\} \quad (10)$$

Motivated by the BMS setback of K not a clearly defined biological parameter of cycle viability and indistinguishable covariate effect values on K and Pd, Dunson (2001) proposed a Bayesian pregnancy probability model as an improvement of BMS. Dunson (2001) extension of the BMS is given in equation below.

$$P = K\{S_m + (1 - S_m)\{1 - \prod_{l=-c}^{d} (1 - P_l)^{S_{l+m}}\}\} \quad (11)$$

K was defined as a cycle viability parameter for determining conception probability given intercourse occurrence S in the most fertile day m and Pl the ratio of conception probability given intercourse on day l to conception probability given intercourse on m. The improvement gives the opportunity for a flexible characterization of covariate effects among couples in daily fecundity.
Improvements of BMS by further research contributions focused on improving the cycle viability parameter K which perhaps gives opportunity to improve the daily conception probability Pd parameter, just like Dunson and Stanford (2005) contribution, where Dunson (2001) conception probability model was improved due to its lack of selective power of categorical predictors levels in determining Pd, therefore a pregnancy probability model was proposed focusing on improving Pd as shown in equation 12.

$$Pd = 1 - exp\{-\xi_i exp(u_{ijd}^{l}\beta)\} \quad (12)$$

Although, the cycle viability parameter was excluded in their proposed model due to the weak and unidentified nature exhibited by the parameter (Dunson and Stanford, 2005), but a random effect ξ in term of daily conception probability was included.ξ represents a fecundity multiplier for couple i, β is a vector of regression coefficient and uIijd is the covariate parameter value in cycle j from couple i. Kim et al. (2012) further generated a more flexible conception probability model using a reparametizedr = $-\xi_i exp(u_{ijd}^{l}\beta)$ as log(r), this is due the probable biased estimates of P caused by the restriction of using the exponential link.
Furthermore, extending the BMS model, models were proposed to estimate the effects of covariates on daily conception probability. Colombo et al. (2006) proposed a model (as in equation 13) for analyzing mucus covariate factor effects on conception probability. Their model proposal was presented to ease the difficulty arising from estimating the large number of cervical mucus score parameters within a twelve (12) days fertile window of a cycle. Such difficulty are experienced by works that analyzes the relationship between discharge mucus types and daily conception probability.

$$P = A^{C_j}.K\{1 - \prod_d (1 - p_d)^{S_d}\} \quad (13)$$

A represents the mucus covariate parameter, where Cj = 1 so as to estimate the mucus score for each cycle j. However, the mucus score model was derived based on the assumption the effects are fixed within a specific fertile window day and thus the effect of the mucus covariate on the daily probability of conception Pd was proposed as in equation 14.

$$Pd = \frac{\exp(\delta_i + AM_{ij})}{1 + \exp(\delta_i + AM_{ij})} \quad (14)$$

Where δi is the effect of conception probability depending on the specific day i while Mij is the dummy variable indicating mucus code in cycle j by couple i.

Further Development

In the last two decades, modelling pregnancy probability have been extended to joint modelling, where fecundity covariates are modelled separately from pregnancy probability using statistical distributions and then a joint model for analyzing the covariate heterogeneity in fecundity is generated.

Kim et al. (2010) proposed a joint model of intercourse covariate heterogeneity and fecundity putting into consideration the restrictive setback of BMS models applications due to the used assumption that each intercourse occurrence in consecutive days in a menstrual cycle contributes independently to achieving conception in that cycle. Thus the proposed joint model focus on understanding intercourse heterogeneity within a menstrual cycle fertile window by accounting for the dependency of intercourse occurrences on consecutive days. Motivated by the intercourse assumption that pregnancy achievement within a menstrual cycle does not only depend on intercourse occurrence within the menstrual cycle fertile window but also intercourse occurrence outside the menstrual cycle fertile window, Lumet al. (2016) used a cubic spline distribution to model details within a menstrual cycle and then proposed a Bayesian Joint Model for menstrual cycle length and pregnancy probability. Lumet al. (2017) extended Lumet al. (2016) work with the inclusion of a modelled distribution of perfluoroalkyl chemical concentration effect. Kim et al. (2019) also developed a joint model of environmental exposures detection limits effect model and pregnancy probability model of Kim et al. (2010).

BMS Resolution on Analyzing Fertility Category

Unlike the TTPs models that analyzes heterogeneity of fecundity and its covariates effects within menstrual cycles at the couples level, BMS models analyzes fecundity heterogeneity and covariates effects at menstrual cycle level across couples putting into account the daily biological and fertilization details of the couples. This best assist fertile couples to understand their chance of getting pregnant with respect to their daily fertilization activities and biological system across a cycle.

BMS Analysis on Subfertility Category

Similar to the TTPs models, BMS was assumed to be applicable to the subfertile couples due to its designed source (data) of both fertile and subfertile couples. Furthermore, irrespective of the fact that subfertile couples needs more than a menstrual cycle to achieve pregnancy, BMS could still be used to estimate the pregnancy probability of a subfertile couple within each of the menstrual cycles needed to achieve pregnancy.

BMS Limitation on Analyzing Subfertility Category

BMS assumed the pregnancy probability estimate within a menstrual cycle is constant across successive menstrual cycles with similar fecundity heterogeneity and covariates details (Barrett and Marshall, 1969). By this assumption, pregnancy probability of a subfertile couple in one cycle is same with other cycles needed to achieve pregnancy, if the daily fecundity pattern in one cycle is maintained in other cycles. The consequence to this assumption is that the pregnancy probability for a fertile couple in a cycle is same with a subfertile couple with similar daily fecundity pattern in a cycle. For instance, if the probability of pregnancy of fertile couple A in cycle A1 with fecundity pattern P(a,b,c) is 0.6 then, the probability of pregnancy of subfertile couple B in cycle B1 with fecundity pattern P(a,b,c) will also be 0.6. The result is not true however, if the definition of subfertility in terms of the number of cycles needed to achieve pregnancy is accounted for in the proposed BMS model. Therefore, there is need for accounting for the number of menstrual cycles needed to achieve pregnancy for subfertile couple when proposing a pregnancy probability model.

Category 3 (DLPP)

The purpose of the introduction of this approach for developing fecunidty prediction is to minimize the scalability problem encountered by earlier TTPs and BMS models (Liu et al. 2019). The deep learning methods used for proposing the DLPP models is the Long-Short Term Memory. This is due the time series nature of fecundity data, and the best deep learning method for time series data as of when the DLPP approach was introduced is the LSTM network. Although, other deep and machine learning methods have been used for fecundity prediction like the DLNN and ANN based fecundity prediction models proposed by Naseem et al. (2023) and Yland et al. (2022) respectively.

DLPP Analysis on Fertility Category

The LSTM based DLPP approach uses same assumptions as the BMS approach for proposing pregnancy probability prediction models, which is accounting for daily fecundity details when predicting fecundity within a menstrual cycle.

Liu et al. (2019) investigated the feasibility of predicting pregnancy using mobile health tracking data from the Clue app, addressing a long-standing challenge in women's health research. They developed four models—logistic regression and three LSTM variants—to estimate pregnancy probability, leveraging a dataset of 79 million logs from 65,276 women with confirmed pregnancy test results. Their models effectively stratified pregnancy risk, with the top 10% of predicted probabilities correlating to an 89% pregnancy likelihood over six cycles, compared to 27% in the lowest 10%. Additionally, they introduced a method to extract interpretable trends from deep learning models, aligning with established fertility research.

Naseem et al. (2023) explores the use of deep learning, specifically convolutional neural networks (CNNs), to improve the accuracy of predicting men's fertility. Traditional semen analysis, based on threshold values for sperm quality, may miss key factors influenced by diet and other conditions. The proposed method segments sperm heads and tracks their movement to assess fertility more accurately. The approach achieves 80.95% accuracy in predicting semen quality and 85.71% accuracy in detecting sperm heads, suggesting that deep learning can enhance fertility assessments and aid in automating artificial insemination processes.

Yland et al. (2022) study developed an ANN and other Machine Learning based models to predict the probability of conception among women actively trying to conceive, using data from a North American preconception cohort. With an AUC of around 70%, the models outperformed previous predictive efforts. Key predictors positively associated with pregnancy were previous breastfeeding and supplement use, while factors like female age, BMI, and infertility history had negative associations. The study highlights the potential of machine learning in improving conception prediction, though it acknowledges limitations like reliance on self-reported data and the absence of external validation.

Wang et al. (2022) investigated the application of machine learning algorithms to predict clinical pregnancy outcomes in

IVF cycles using a large dataset of 24,730 patients from Taipei Medical University Hospital. Their study compared the performance of random forest and logistic regression models, finding that the random forest algorithm achieved superior predictive accuracy, with the ovarian stimulation protocol identified as the most influential factor, particularly long and ultra-long protocols, which positively impacted pregnancy success. Additionally, the number of frozen and transferred embryos was positively associated with clinical pregnancy, while female age and infertility duration had negative effects.

Zhan et al. (2022) study focused on developing a predictive model to assess fecundity (the ability to conceive) based on several infertility-related factors in expectant couples. Researchers included 410 couples from a hospital in Xinjiang, China, conducting a one-year follow-up to track female pregnancy outcomes. The sample was divided into a model group and a test group to validate results. Factors identified as significant in predicting fecundity included female age, occupational stress, gynecological diseases, anti-Müllerian hormone (AMH), follicle-stimulating hormone (FSH), fasting plasma glucose (FPG), depression, and male smoking habits.Using logistic regression and LASSO regression analyses, the model achieved high accuracy, with the area under the curve (AUC) values ranging between 0.917 and 0.955 across different groups. These AUC scores indicate strong predictive power, suggesting the model can effectively discriminate between higher and lower fecundity risks.

Tarin et al. (2020) study aimed to create a predictive model to assess the chances of successful live birth (LB) for women before starting their first IVF or ICSI cycle. By examining two extreme prognostic groups—women who had an LB in their first cycle and those who failed after three cycles—the researchers sought to identify significant predictors of assisted fecundity.The study included 708 women, divided into a development group (531 women) and a validation group (177 women). Using logistic regression with forward-stepwise selection, the model incorporated seven predictors: age, multiple infertility factors, antral follicle count, smoking status, irregular menstrual cycles, and baseline prolactin and LH levels. The model's performance, measured by the c-statistic, was 0.718 in the development group and 0.649 in the validation group, indicating moderate predictive accuracy.

Muhammad et al. (2023) conducted research to address limitations in fecundity prediction by proposing a hybrid data collection approach to overcome the challenges of small dataset size and low dimensionality in existing fecundity datasets, as well as refining the subfertility definition used in developing User-embedding LSTM-based prediction models. Their study generated a larger and more robust fecundity dataset, which was then used to implement and evaluate both existing and improved LSTM-based models. The proposed model demonstrated superior performance, as evidenced by better AUC-ROC evaluation results.

Kassaw et al. (2025) investigated the application of machine learning (ML) models to classify fertility rates and identify key predictors among reproductive-age women in Ethiopia using data from the 2019 Ethiopian Demographic Health Survey (EDHS). The study employed eight ML models, developed in Python, with performance evaluated through metrics such as accuracy, AUC, precision, recall, and F1-score. The random forest classifier emerged as the top-performing model, followed by a one-dimensional convolutional neural network, logistic regression, and gradient boost classifier. Key predictors of fertility included family size, age, occupation, and education. The findings highlighted the potential of ML in fertility prediction and underscored socioeconomic factors as critical targets for public health interventions.

Zhu et al. (2022) investigated the fertility behaviors of China's floating population using data from the 2016 China Migrants Dynamic Survey, employing logistic regression, multiple linear regression, artificial neural networks (ANN), and naive Bayes models to analyze influencing factors and predict reproductive decisions. Their findings revealed that demographic, socioeconomic, and migration-related factors—such as age, education, occupation, duration of residence, and economic conditions—significantly influenced fertility behaviors, with longer post-migration residence and better economic status positively correlating with higher fertility likelihood, while highly educated non-agricultural workers in first-tier cities exhibited lower fertility intentions. The ANN and logistic regression models demonstrated strong predictive accuracy, suggesting their utility in urban population management.

Kelsey et al. (2022) developed a predictive model to estimate the age at which Premature Ovarian Insufficiency (POI) would occur in young female cancer patients undergoing pelvic radiotherapy, integrating an updated, externally validated model of ovarian reserve decline with the median lethal dose (LD50) for the human ovary. By utilizing the patient's age at diagnosis and the radiotherapy treatment plan to estimate ovarian dose, their algorithm generated personalized predictions of POI onset, which were made accessible via an online calculator to facilitate fertility risk counseling. The study illustrated the model's application through four case examples, comparing photon and proton therapy plans in terms of their impact on remaining fertile lifespan, emphasizing the importance of fertility considerations in pediatric oncology guidelines.

Kim (2023) investigated factors influencing pregnancy intention among reproductive-aged women in Korea using data from the Korean National Health and Nutrition Examination Survey (KNHANES), which included 22,731 women aged 15–49. To address confounding by age and birth year, the study employed propensity score matching and utilized the XGBoost model to identify key predictors, revealing weekly working hours as the most significant factor. Cluster analysis categorized women into three groups, with those working an average of 34.4±12.9 hours per week showing the highest pregnancy likelihood. Logistic regression further demonstrated that women working 35–45 hours weekly had significantly higher odds of pregnancy compared to those working other hours, underscoring the impact of excessive work hours on fertility intentions. The study highlighted Korea's long workweek relative to OECD standards and proposed stricter regulation of working hours and telecommuting options as potential policy measures to improve fertility rates.

DLPP Analysis on Subfertile Couples

Unlike TTPs, BMS and some DLPP models, LSTM based DLPP assumes pregnancy probability of subfertile couple within a menstrual cycle does not account for the complete historic fecundity heterogeneity of the subfertile couple, therefore fecundity details of prior menstrual cycles to the current menstrual cycle needs to be analyzed to determine the accurate pregnancy probability of a subfertile couple (Liu et al., 2019).

Using this assumption Liu et al. (2019) proposed a pregnancy probability prediction model using a user-embedding LSTM (containing an analysis of fecundity details within 6 menstrual cycles, that is, 180 cycles' days) concatenated with another LSTM (containing the analysis of fecundity details of the current cycle). As described in figure 1, the proposed model User Embedding Long Short Term Memory (LSTMUE) architecture enables the estimation of the pregnancy probability by accounting for not only the fecundity heterogeneity of the current cycle but also the last six (cycles).

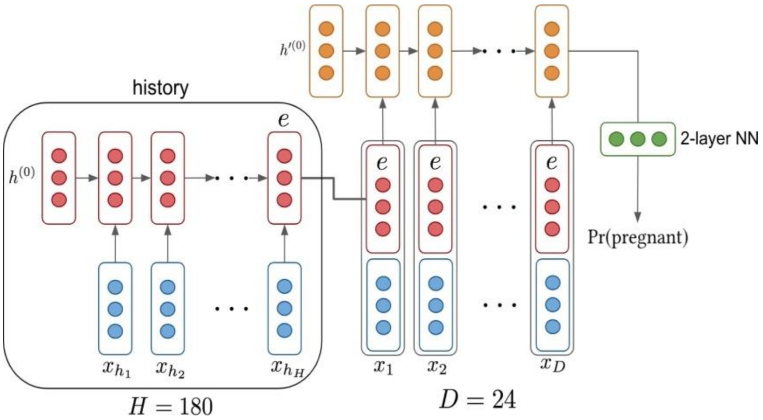

Figure 1: LSTMUE architecture (Liu et al., 2019)

DLPP incorporated the definition of subfertility in term of number of menstrual cycles needed to achieve pregnancy with its proposed model for predicting fecundity. However, the proposed model focused on analyzing only seven (7) cycles whereas a couple is said to be subfertile for a period of 12 menstrual cycles before considered as clinical infertile (Van der steeg et al., 2006), so therefore, a more accommodating DLPP model architecture is needed to accommodate the benchmark menstrual cycles number needed to achieve pregnancy for subfertile couples.

CONCLUSION

Fecundity prediction models were developed to support the process of predicting fecundity, however, the proposed fecundity models are bound to exhibit certain limitations. To help identify such limitations, the proposed models and data used for validating the proposed models or used for analyzing fecundity amongst couples are reviewed. In this study review, proposed fecundity models were reviewed in three categories Although, it was observed that the TTPs and BMS fecundity analysis models focuses more on analyzing the fecundity heterogeneity among fertility categorized couples but the proposed fecundity models unsatisfactorily analyzes the fecundity heterogeneities among subfertility categorized couples (Muhammad et al., 2023; Liu et al., 2019). On the other hand, DLPP models focuses on analyzing the fecundity heterogeneity among fertile and subfertile couples, but explicitly distinguishing fertility and subfertility from analyzing same dataset is still a problem to be resolved (Muhammad et al., 2023). Furthermore, some fertility influencing factors are yet to be explicitly studied to understand how they influence fertility; like woman's history of pregnancies, women menstrual cycle lengths' dynamicity.

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