Validating a Machine Learning Model to Predict Live Birth After Vitrified Donor Oocyte IVF

Authors: Vanessa Pataia,[1] Mylene W.M. Yao,[2] Elizabeth T. Nguyen,[2] Marta Wolska,[1] Trina Shah,[1,3] Hemlata Thackare,[1] Shailaja Nair,[1] Nick Macklon,[1,3] *Kamal Ahuja[1,3]

1. London Egg Bank, UK
2. Univfy, Los Altos, California, USA
3. London Women's Clinic, UK
*Correspondence to kamal.ahuja@londonwomensclinic.com

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Keywords: Donor oocytes, egg donation, live birth prediction, machine learning (ML), vitrified oocytes.

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BACKGROUND AND AIMS

Age-based counselling remains standard practice for prospective recipients of donor oocyte IVF, despite substantial variability in outcomes that age alone cannot capture.[1] While machine learning (ML) methods have improved outcome prediction in autologous IVF,[2-4] their application to donor oocyte cycles has not been explored. A team from London Egg Bank, UK; and Univfy, Los Altos, California, USA, set out to determine whether an ML model built from donor and recipient clinical characteristics could predict the likelihood of live birth per embryo transfer (ET) more accurately than age-based counselling.

MATERIALS AND METHODS

The retrospective cohort study analysed 3,036 ETs performed for 1,958 recipients using vitrified oocytes from 1,135 donors between 2017–2022, drawn from a UK-regulated vitrified donor oocyte programme. Gradient boosted machine models were developed and validated using five-fold cross-validation to predict live birth per ET. Two prediction models were built: a pre-treatment model, using variables available before treatment began, and a pre-ET model, incorporating variables known immediately before transfer. Both were compared against three age-based control models: recipient age alone, donor age alone, and combined recipient and donor age (RDA).

RESULTS

The best prediction model, the pre-ET model, outperformed RDA, the best-performing age control, achieving a 14.9% improvement in receiver operating characteristic area under the curve (0.50 versus 0.45) and a 12.3% improvement in precision-recall area under the curve (0.50 versus 0.45), reflecting stronger discrimination and prediction of live birth events. Across higher live birth probability thresholds (from 51% upwards), both the pre-treatment and pre-ET models achieved higher F1 scores than any age-based control, indicating a superior overall ability to minimise false positives and false negatives. At a threshold of 58% or above, for example, the pre-treatment and pre-ET models scored 0.26 and 0.45 respectively, compared with 0, 0, and 0.07 for the recipient-age, donor-age, and RDA models.

Predictor relative importance analysis of the pre-ET model identified the total number

of usable embryos as the most influential variable, accounting for 45% relative importance, ahead of recipient ET number (16%), recipient age (11%), donor age (11%), and donor anti-Müllerian hormone (9%). This ranking challenges the assumption that age is the primary determinant of outcome in donor oocyte cycles, suggesting embryo yield and treatment history carry greater predictive weight.

Observed live birth rates were 43% after a first ET, decreasing to 34–36% in subsequent transfers. Cumulative analysis of the 1,336 recipients (68% of the cohort) who underwent up to three ETs found a cumulative live birth rate of 87.7%, underscoring the value of encouraging treatment continuation where clinically appropriate.

LIMITATIONS

The authors acknowledge limitations. The cohort was drawn from a limited number of UK centres, which may reflect centre-specific practice and selection criteria, and the outcome modelled was live birth per ET rather than cumulative live birth, since recipients could receive oocytes from more than one donor and varying oocyte numbers.

CONCLUSION

These findings support a shift away from age-based counselling alone toward individualised, ML-informed prognostic tools for donor oocyte IVF. Incorporating variables such as embryo yield, treatment history, and donor AMH into patient counselling could help calibrate expectations more precisely and support shared decision-making between clinicians and recipients. The authors suggest that further work should explore additional biological markers to refine prediction accuracy, and that prospective validation across a broader range of centres would strengthen the case for clinical implementation of ML-based prognostic counselling in this setting.

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