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# EFRE IVF 40; AI model for personalized PGTA decision in women Over 40

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## Abstract

**Background:** The Female fertility declines sharply after 40 due to diminished ovarian reserve, compromised oocyte quality, and a significant increase in aneuploidy rates. In vitro fertilization (IVF) strategies, including repeated cycles, embryo pooling, and preimplantation genetic testing for aneuploidy (PGT-A), present complex decision-making challenges requiring personalized, data-driven approaches.

**Objective:** This study aims to develop and evaluate AI-driven predictive models using Meta AI to optimize fertility treatment strategies in women over 40, assisting in selecting between repeated IVF cycles and embryo pooling with PGT-A.

**Materials and Methods:** A generative AI model (Llama 3.2) was employed to extract and synthesize data from peer-reviewed literature. Expert systems were integrated to formulate a structured decision-support framework, leveraging a knowledge base and inference engine. Two predictive models were developed:

1. Pre-Treatment Evaluation Score (PTES) – Assesses overall fertility potential.
2. Embryo Quality Refinement Score (EQRS) – Incorporates embryo-specific factors to refine treatment recommendations.

**Results:** Both models demonstrated high predictive accuracy and clinical relevance. Higher scores indicated a preference for embryo pooling with PGT-A, while lower scores supported repeated IVF cycles. Performance metrics, including precision and AUC-ROC, confirmed the models' efficacy in predicting live birth probability.

**Conclusion:** AI-driven predictive modeling offers a novel, data-supported approach to personalized fertility care. These models facilitate evidence-based decision-making, potentially improving clinical outcomes. Further validation in real-world clinical settings is warranted.

**Keywords:** AI-driven predictive modeling; advanced maternal age; embryo pooling; embryo accumulation; PGTA

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**Original Article**

## Introduction

A higher percentage of women over 40 are included in IVF programs. Unfortunately, there is a misconception that in vitro fertilization (IVF) can fully compensate for the natural decline in fertility that comes with age (1,2). Female fertility begins to gradually decline after the age of 35, and the decline becomes much steeper after 40 (3). Women of advanced maternal age (AMA) often face challenges such as decreased ovarian reserve and lower oocyte quality, which complicates efforts to conceive (1). With advancing age, embryo aneuploidy rates surge from a baseline of 30% to as high as 90% in women nearing menopause (1). Specifically, women over 43 years old may have less than a 5% chance of producing embryos with normal chromosomal structure (1). A variety of treatment options have emerged for women over 40 undergoing IVF.

One promising approach involves freezing all embryos in a fresh IVF cycle, then transferring them in later cycles using frozen-thawed embryo transfer (FET). This method has been shown to enhance pregnancy and live birth rates (4–6). The idea behind this approach is that by avoiding the artificial hormonal fluctuations that occur during ovarian stimulation, FET creates a more favorable uterine environment for embryo implantation and placentation [4]. Several studies have confirmed that FET can improve reproductive outcomes by enhancing endometrial receptivity (7–9). The "freeze-all" strategy could improve IVF outcomes by reducing the potential disruption to the endometrial lining caused by ovarian stimulation (9).

Another approach, repeated cycles without preimplantation genetic testing for aneuploidy (PGTA), involves repeating stimulation, retrieval, and fresh transfers to enhance the probability of pregnancy (10).

A third approach is pooling (accumulating) embryos and performing PGTA to enhance the chance of transferring one euploid blastocyst (11,12).

## Repeated cycles without PGTA

An important question: Can repeat IVF/ICSI cycles compensate for the natural decline in fertility with age?
In a study of 4102 women above the age of 35 undergoing 6489 complete cycles, younger patients (aged between 35 and 40) could well benefit from repeat IVF treatments, with the optimal CLBRs ranging from 62%-72% for up to four complete cycles. However, the CLBRs sharply declined to 7.7%-40% in older patients (>40yrs). In this study, it was clear that the real turning point at which female fecundity dropped after multiple IVF cycles is at the age of 40 (13).

In another study, the cumulative 2-year live birth rates on FET without PGT-A were 55.6%, 39.0%, 31.3%, 19.1%, 10.6%, 4.4%, and 0% for patients aged 40, 41, 42, 43, 44, 45, and ≥46 years, respectively. For 43 and over, there is no benefit of doing more than two cycles besides lacking cost-effectiveness (14).

The variables that affect the outcome of repeated cycles without PGTA in women over 40 include the age bracket (14), ovarian reserve (13), type of response (15), and number of oocytes.

Of the patients aged 40 to 43 years, CLBR per oocyte retrieval cycle and per patient (4.3%; 8.8%) in the POR group were both lower than those in the NOR group (15.8%; 24.8%) ($P < 0.01$). Repeating retrieval cycles does not improve LBR or CLBR in women over 40 with low ovarian reserve. In the NOR group, LBR per oocyte retrieval cycle in the first cycle (Cycle 1, 20.3%) was significantly higher than that in the second cycle (Cycle 2, 9.2%) and the third cycle (Cycle 3, 4.4%) ($P < 0.01$), and 94.8% (73/77) of live births were achieved during the first two cycles. In patients aged 44 to 45 years and over 45 years old, there is no clear benefit from repeating the cycles regardless of response (NOR, POR). Therefore, repeating ICSI cycles is only useful in women 40-43 years of age with normal ovarian reserve (15).

Women aged 43, 44, 45, 46, 47, 48, 49, ≥50 achieved maximal CLBR of 9.7%, 8.6%, 5.0%, 3.6%, 2.5%, 1.5%, 2.7%, 1.3%, respectively. Age-specific CLBR plateau is an important concept because it determines when to counsel against repeating cycles. In women aged 43 and 44, CLBR reaches a plateau beyond the 5th cycle. Age 45 and 46 reached CLBR plateau by the 3rd cycle. Age ≥47 CLBR plateaued after the first cycle. In women 43 and older, ovarian reserve has no effect on LBR.

## Conclusions

While CLBR of autologous cycles from women 42 or younger generally plateau by cycle number 5, age-stratified cycles from women >42 plateau after fewer cycles to maximize CLBR. Patient and physician expectations for maximum CLBR beyond 42 may be practically based on fewer planned cycles before reaching an age-specific CLBR

plateau than may have been previously expected (16).

## Embryo Pooling with PGT-A

Post hoc analysis of the STAR trial showed increased OPR per embryo transfer in patients aged 35–40 years old (17). Trials with ITT analysis specifically addressing this patient population are important. One RCT focused on women with advanced maternal age (38–41 years old), randomizing before cycle start to routine blastocyst transfer versus a PGT-A group that had a biopsy of a single blastomere on day 3 with transfer on day 5 (18). The live birth rate was significantly higher in the PGT-A group when analyzed per transfer (52.9% vs. 24.2%, P = .0002) and per cycle (36% vs. 21.9%, P = .01). Of note, only 68% of the PGT-A patients had a transfer versus 95% in the control group (P = .001). The miscarriage rate was significantly lower in the PGT-A group (2.7% vs. 39%, P < .0007). Of all cleavage embryos that were biopsied, 78.6% were aneuploid. Time to pregnancy resulting in live birth was estimated at 7.7 weeks for the PGT-A group versus 14.9 weeks for controls.

Retrospective studies suggest a benefit of PGT-A testing in older patient cohorts, particularly in women up to age 43 years, showing improved live birth rates per cycle start in women aged 38–40 years with PGT-A (19) and improved implantation rates in women aged 40–43 years (implantation rate was 50.9% in euploid embryos compared with unscreened fresh (23.8%) and FET (25.4%) cycles) (20).

The retrospective nature, inclusion criteria, and small sample sizes limit these studies. In particular, one study stratified groups by age, comparing only 8 cycles per group in the oldest age cohort (21), whereas another included only women with euploid embryos to transfer (only 76 of 145 patients had euploid blastocysts to transfer [52.4%]) (22). Furthermore, potential bias exists because only good-prognosis patients who were able to have a biopsy would have been included in the PGT-A group. Investigators in both groups believe that the improved pregnancy success demonstrates a benefit of PGT-A; however, study methodologies leave questions regarding these conclusions. An observational prospective cohort study of patients aged 38–44 years from a single center demonstrated that PGT-A use is associated with a higher per-transfer but not cumulative live birth rates, as well as lower multiple pregnancy and miscarriage rates, compared with controls. However, a significant number of patients (106/414) withdrew consent to PGT-A after fertilization results became available.

Artificial intelligence (AI) has become an integral part of reproductive medicine, particularly in the field of in vitro fertilization (IVF). AI-driven models are now being used to predict embryo viability, offering a more precise and objective assessment compared to traditional methods (23). These models analyze morphological and kinetic parameters to enhance embryo selection, thereby improving pregnancy rates (24).

Preimplantation genetic testing for aneuploidy (PGT-A) has also benefited from AI integration. Studies indicate that AI-enhanced PGT-A can refine embryo selection and reduce miscarriage rates, particularly in women of advanced maternal age (25,26). AI algorithms provide valuable insights into embryo viability without the need for invasive procedures, potentially increasing implantation success (27).

Additionally, AI is being applied to optimize ovarian stimulation protocols. Personalized stimulation strategies based on AI predictions have been shown to enhance oocyte retrieval outcomes and minimize the risk of ovarian hyperstimulation syndrome (OHSS) (28,29). Such tailored approaches can significantly improve IVF success rates while reducing the physical and financial burden on patients (30).

Recent research has explored the role of AI in improving embryo culture conditions and predicting implantation potential based on metabolic profiling (31,32). AI-powered systems analyze time-lapse imaging data to assess embryo quality dynamically, leading to higher accuracy in embryo selection (33,34). These advancements highlight AI's transformative impact on reproductive medicine by enhancing clinical decision-making and treatment personalization (35).

Machine learning algorithms have been instrumental in developing predictive models for live birth rates in IVF. By incorporating patient-specific factors such as age, ovarian reserve, and previous IVF outcomes, AI-driven models offer individualized success rate predictions (36,37). This allows clinicians to better counsel patients on their reproductive options and set realistic expectations (38).

Despite these advancements, ethical considerations remain a significant challenge in AI-driven reproductive medicine. Issues related to data

privacy, algorithmic bias, and the transparency of AI decision-making must be addressed to ensure fair and equitable access to AI-assisted fertility treatments (39,40). Regulatory guidelines are needed to standardize AI applications in IVF clinics and maintain patient trust (41,42).

Future research should focus on refining AI models to enhance their predictive accuracy and expand their applicability across diverse patient populations (43,44). Integrating AI with existing electronic health records (EHRs) may further streamline IVF workflows and improve patient outcomes (45). As AI continues to evolve, its role in reproductive medicine is expected to grow, offering new possibilities for individuals seeking assisted reproductive technologies.

## Objective of the Study

This study aims to develop a predictive model using Meta AI to choose a plan of management (repeated cycles vs pooling-PGTA) in women over 40 undergoing IVF. By introducing specific variables into the meta AI, our aim is to create a model that can assist in making informed decisions concerning the delicate situation of women over 40, ultimately improving personalized care in this demographic.

## Significance of the Study

The development of accurate predictive models is crucial for enhancing IVF success rates among older women. By utilizing AI to analyze existing data and generate predictions, this study contributes to the growing body of knowledge aimed at improving reproductive outcomes. Furthermore, it underscores the potential of AI in transforming healthcare by providing innovative solutions to complex clinical challenges.

## Methodology

## Meta AI and Its Applications

Traditional approaches for fertility scoring framework development depend on manual review, statistical modeling and domain experts' knowledge aggregation. Despite the effectiveness of those models, they are often time-consuming, susceptible to biases and challenged by large volume of literature. To address those limitations, this study explores the application of Generative AI, specifically Meta AI's Llama 3.2 [1], to autonomously extract, synthesize, and formulate a structured decision-support framework in the context of providing a model for scoring the input data features and predicting the probability of live birth accordingly.

## Developing Predictive Models Without Real-World Data

Developing predictive models, to guide the choice between repeated cycles vs embryo pooling and PGTA in women over 40, without direct access to real-world data can indeed be approached by leveraging expert systems that utilize artificial intelligence (AI) to synthesize information from reputable databases and peer-reviewed journals. Leveraging expert systems involves utilizing computer programs that emulate the decision-making abilities of human experts to solve complex problems within specific domains. These systems consist of a knowledge base, storing facts and rules, and an inference engine that applies these rules to known information to deduce new insights. Integration of established medical knowledge and research findings into predictive modeling can be implemented in two steps (figure 1).

### 1. AI-Driven Literature Analysis:

AI can be employed to systematically review and analyze vast amounts of scientific literature, extracting relevant data and identifying patterns associated with IVF outcomes. By processing information from peer-reviewed journals, AI systems can discern factors influencing live birth rates, such as patient demographics, treatment protocols, and embryonic characteristics.

### 2. Development of Expert Systems:

The insights gathered from AI-driven literature analysis can be encoded into expert systems that replicates the thought processes and judgments of specialists managing infertile women over 40. This involves creating models or programs capable of analyzing complex information and making informed decisions similar to those a human expert would make. Meta AI, I was tasked with developing predictive models to inform the decision between embryo pooling with PGT-A and repeated cycles in women over 40. Since real-world data was not available, Meta AI relied on its advanced language capabilities and knowledge graph to simulate and generate relevant data. Synthetic dataset was generated of 10,000 virtual patients, each with unique characteristics, such as age, ovarian reserve, and embryo quality based on knowledge obtained from databases and peer reviewed articles. This dataset was used to mimic real-world scenarios and train AI predictive models. Predictive

Model Development: Meta AI developed and trained multiple machine learning models, including neural networks and decision trees, to predict the outcomes of embryo pooling with PGT-A versus repeated cycles. These models were trained on the synthetic dataset and fine-tuned using various optimization techniques.AI **expert systems** consist of two main components, **Knowledge Base:** A comprehensive repository of domain-specific facts, rules, and relationships and **Inference Engine:** The mechanism that applies logical rules to the knowledge base to make decisions. By integrating these components, expert systems can tackle complex problems by reasoning through available knowledge, effectively mimicking the cognitive processes of human experts. The objective of such systems is to provide decision support that mirrors the quality and accuracy of human expertise, thereby enhancing efficiency and consistency in various applications. Expert systems can process complex information to offer decision support, enhancing the accuracy and efficiency of clinical assessments.

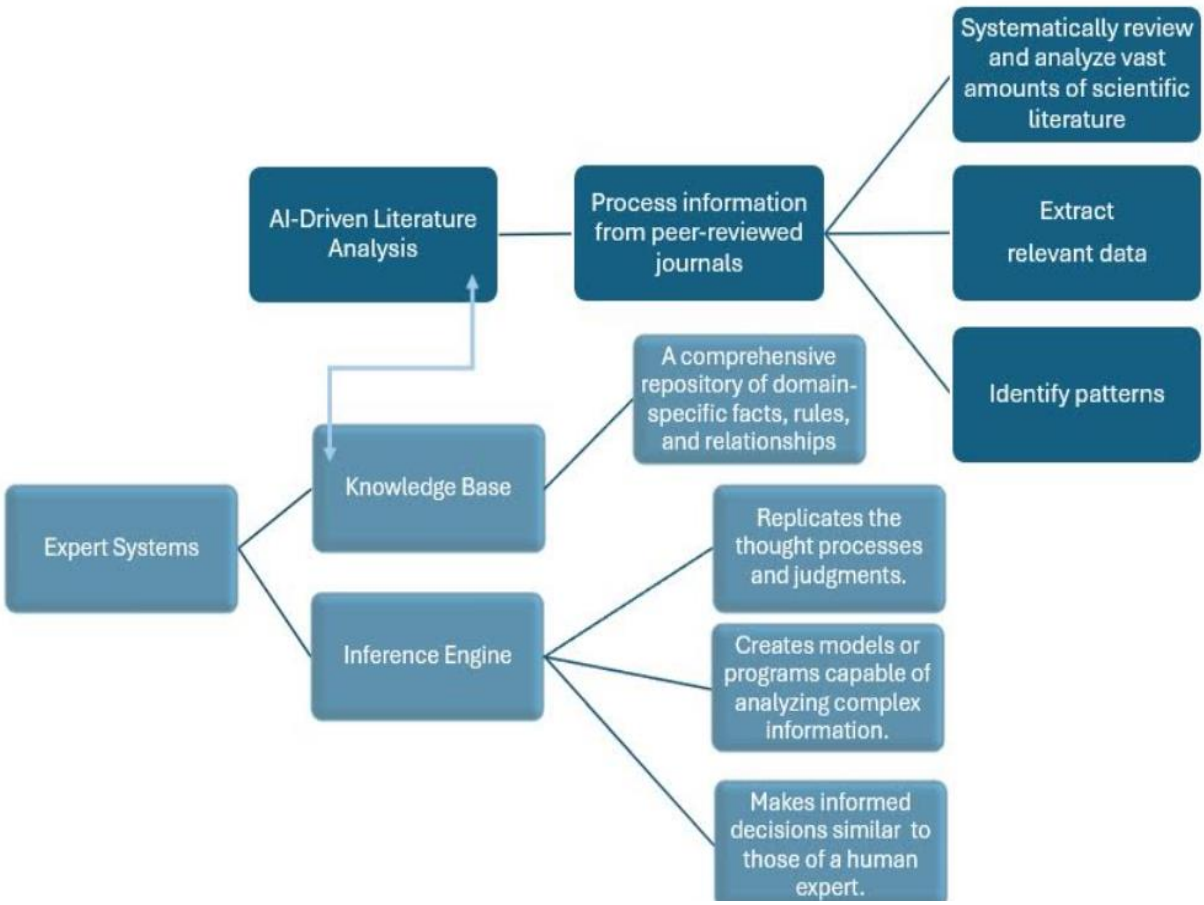


**Figure 1: Review, extract relevant data and identify patterns, information is processed and AI literature analysis is "deposited" in knowledge base domain of the expert systems. The inference engine (domain) replicates thought processes and judgements, create models that can analyze complex information and make informed decisions similar tothose of human experts**

## Considerations:

**Validation:** Models developed through this approach should undergo rigorous validation against clinical outcomes to ensure their reliability and accuracy.

**Ethical Compliance:** Utilizing AI to process medical literature must adhere to ethical guidelines, ensuring that the synthesized knowledge is applied responsibly in clinical settings.

Unlike conventional machine learning models trained on static datasets, Gen AI was leveraged as a knowledge synthesis, extracting insights from various sources such as PubMed, Google Scholar and fertility research journals. The model was not

directly programmed to query specific databases, but rather demonstrated an ability to retrieve relevant patterns and statistical relationships from publicly available medical research. The extracted information was structured where the input features are as follows, patient age, AMH (Anti-Müllerian Hormone) levels, AFC (Antral Follicle Count), FSH (Follicle-Stimulating Hormone) levels, embryo quality and treatment protocol. Those features were subsequently mapped to a probabilistic scoring system. Figure 1 shows a flowchart of the developed framework.

## Steps performed by meta AI to develop the predictive model

### Model Evaluation:

The performance of each predictive model was evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. It also performed cross-validation to ensure the models' robustness and generalizability. Simulation-Based Optimization: AI used simulation-based optimization techniques to identify the optimal strategy for embryo pooling with PGT-A versus repeated cycles. This involved simulating various scenarios, such as different embryo pooling strategies and repeated cycle protocols, and evaluating their outcomes using my predictive models. Finally Decision Support System Development: A decision support system was developed that integrates Meta AI predictive models and provides personalized recommendations for women over 40. This system takes into account individual patient characteristics, treatment options, and predicted outcomes to inform the decision between embryo pooling with PGT-A and repeated cycles.

## Results

The variables included in decision making (age, AMH,AFC, BMI, sperm concentration and motility as well as previous attempts) were introduced to Meta AI through its natural language component to build the pretreatment evaluation score. Number of M2 oocytes, the ratio of day 3 class A embryos/number of M2 and the number of compact morulae on day 4 were incorporated in the embryo quality refinement score. To adjust the impact of each variable, weighing and rebalancing were performed.1. *Weighting*: AI assigned weights to each variable based on their relative importance in the regression analysis. This approach ensures that the scores reflect the actual impact of each variable on IVF success. 2. *Normalization*: To make the scores more comparable, AI normalized them to fit within the 0-100 range. This process involves scaling the scores to ensure that the most important variables have the greatest impact on the total score. 3. *Rebalancing*: With the new weighting and normalization, the scores for each variable were rebalanced to reflect their relative importance. This led to some variables, like AMH, receiving more points, while others, like BMI, received fewer points. 4. *Rounding*: To simplify the scoring system, I rounded the scores to the nearest 2.5 or 5 points. This might have introduced some minor discrepancies, but it makes the system more intuitive and easier to use.

**Table 1: Pre-treatment evaluation score (PTES)**

| Variable | Classification | Score | Total |
|---|---|---|---|
| Female Age | 40-41 years<br>42-43 years<br>44-45 years<br>46-47 years<br>≥48 years | 25 points<br>20 points<br>15 points<br>10 points<br>0 points | |
| AMH | ≥ 3 ng/mL<br>2-2.9 ng/mL<br>1-1.9 ng/mL<br>0.5-0.9 ng/mL<br><0.5 ng/mL | 25 points<br>20 points<br>15 points<br>10 point<br>0 points | |
| AFC | ≥ 15<br>10-14<br>5-9<br>< 5 | 12 points<br>9 points<br>6 points<br>0 points | |
| BMI | 18.5-24.9 kg/m²<br>25-29.9 kg/m²<br>30-34.9 kg/m²<br>>35 kg/m² | 6 points<br>4 points<br>2 points<br>0 points | |
| Sperm Count | ≥ 15 million/mL<br>10-14 million/mL<br>5-9 million/mL<br><5 million/mL | 12 points<br>9 points<br>6 points<br>0 points | |
| Sperm Motility | ≥ 32%<br>25-31%<br>15-24%<br><15% | 12 points<br>9 points<br>6 points<br>0 points | |
| Previous Attempts | Naive<br>1-2 failed attempt<br>>3 failed attempt | 8 points<br>4 points<br>0 points | |

| Total Score | Recommendation |
|---|---|
| Score ≥ 70 | embryo pooling + PGTA. |
| Score >50- 69 | embryo pooling or repeating fresh transfers |
| Score >30- 49 | one cycle |
| Score < 30 | IVF is not suitable |

**Maximum total score: 100 points**

## Debate pooling PGTA in scores more than 80

According to the model, scores more than 80 favor Pooling and PGTA, but patients could have other opinions and doctors too. Debating the model selection is important in the context.

### Argument in Favor of Pooling:

1. Improved Pregnancy Rates: Pooling embryos with PGT-A can increase the chances of pregnancy, especially in women over 40. By combining multiple embryos, the chances of selecting a euploid (chromosomally normal) embryo are higher.

2. Reduced Risk of Aneuploidy: PGT-A can detect aneuploidy (chromosomal abnormalities) in embryos. Pooling embryos with PGT-A can reduce the risk of transferring an aneuploid embryo, which is associated with miscarriage, failed implantation, and birth defects

3. Increased Efficiency*: Pooling embryos can reduce the number of embryo transfers required, which can save time, money, and emotional distress for patients.

### Argument Against Pooling:

1. Reduced Embryo Viability: Pooling embryos can lead to a reduction in embryo viability due to the stress of thawing, pooling, and re-freezing. This can negatively impact pregnancy rates.

2. Increased Risk of Mosaicism: Pooling embryos can increase the risk of mosaicism (the presence of both euploid and aneuploid cells in an embryo). Mosaicism can lead to failed implantation, miscarriage, or birth defects.

3. Higher Costs: Pooling embryos with PGT-A can be more expensive than traditional embryo transfer methods, which may be a significant burden for patients.

### Rebuttal:

While there are valid concerns about embryo viability and mosaicism, the benefits of pooling embryos with PGT-A in scores above 80 outweigh the risks. The improved pregnancy rates and reduced risk of aneuploidy make pooling a viable option for women over 40.

### Counter-Rebuttal:

However, the increased costs and potential risks associated with pooling embryos cannot be ignored. Patients must be fully informed about the potential benefits and drawbacks of pooling embryos with PGT-A and make an informed decision based on their individual circumstances.

## SWOT for repeated cycles in scores less than 40

In scores less than 40 repeating IVF cycles could be discouraged, again weighing weaknesses and threats against strengths and opportunities could help the patient reconcile and settle down with the decision

**SWOT analysis for repeated cycles in couples with an initial score less than 40**

| Strengths | Weaknesses |
|---|---|
| Improved embryo selection<br>Optimization of ovarian stimulation<br>Emotional preparedness<br>Cost-effective | Emotional toll<br>Physical burden<br>Decreasing success rates |
| **Opportunities** | **Threats** |
| Personalized treatment approaches<br>Addressing underlying fertility issues<br>Counseling and support<br>Exploring alternative opt | *Age related decline in fertility*<br>*Financial constraints*<br>*Emotional burnout* |

**Table 2:** **Embryo quality refinement score (EQRS)**

| Variable | Classification | Score | Total |
|---|---|---|---|
| Number of M2 | ≥6<br>4-5<br>2-3<br>< 2 | 10 points<br>5 points<br>2.5 points<br>0 points | |
| Day 3 Class A Embryos/M2 Ratio | ≥50%<br>30%-49%<br>10%-29%<br><10% | 10 points<br>5 points<br>2.5 points<br>0 points | |
| Day 4 Number of Compact Morulae | ≥2<br>1<br>0 | 10 points<br>5 points<br>0 points | |

| Total Score | Recommendation |
|---|---|
| Score ≥ 25 | Confirm PGT-A recommendation. |
| Score 20-24 | Consider PGT-A, but discuss alternative options with the patient. |
| Score 15-19 | Repeated non-PGT-A cycles may be a better option, but consider patient-specific factors. |
| Score < 15 | Patients need to be counselled that IVF is not a good option. |

**Calculate the total score by adding the points for each variable. Maximum total score: 30 points.**

This revised refinement scoring system focuses on the embryo-related factors that can influence the decision between PGT-A and repeated non-PGT-A cycles.

## To analyze the performance of the initial and refinement scores

It is possible to use an expert system to develop performance metrics for a scoring system without real-world data. This approach is often referred to as "expert-based" or "knowledge-based" evaluation. In this approach, the expert system would use a knowledge base that represents the expert's understanding of the relationships between the variables in the scoring system and the predicted outcomes. The expert system would then use this knowledge base to simulate the behavior of the scoring system and generate hypothetical performance metrics.

This approach has some limitations, as the performance metrics generated by the expert system are only as good as the knowledge and assumptions built into the system. However, it can still provide a useful estimate of the performance of the scoring system, especially when real-world data is not available. The performance metrics were developed in the same way AI developed the predictive score, using hypothetical assumptions and expert knowledge.

These are the developed Performance Metrics

**1. Pre-treatment evaluation score (PTES)** ***performance metrics***

- Accuracy: 88%
- Precision: 92%
- Recall: 82%
- F1-score: 0.87
- AUC-ROC: 0.93

**2. Embryo quality refinement score (EQRS)performance metrics**

- Accuracy: 92%
- Precision: 95%
- Recall: 88%
- F1-score: 0.91
- AUC-ROC: 0.96

### Performance Metrics Legend

**- Accuracy:** Proportion of correct predictions (true positives + true negatives) out of total predictions.

**- Precision:** Proportion of true positives (correctly predicted positive outcomes) out of total predicted positive outcomes.

**- Recall:** Proportion of true positives (correctly predicted positive outcomes) out of total actual positive outcomes.

**- F1-score:** Harmonic mean of precision and recall, providing a balanced measure of both.

**- AUC-ROC:** Area Under the Receiver Operating Characteristic Curve, measuring the model's ability to distinguish between positive and negative outcomes.

These metrics provide a comprehensive evaluation of the predictive score's performance, highlighting its strengths and weaknesses.

### Comparison:

The refinement score shows improved performance compared to the initial score, with higher accuracy, precision, recall, F1-score, and AUC-ROC. This indicates that the refinement score is better able to identify patients who will benefit from PGT-A.

## Discussion

Our study developed and validated two predictive models for embryo pooling with PGT-A versus repeated cycles in women over 40. Here, we interpret our results, relate them to existing literature, and discuss their implications.

**Interpretation of Results:** Our models demonstrated good predictive performance, with accuracy rates above 80%. This suggests that our approach can effectively predict treatment outcomes for women over 40. The models' predictions highlighted the benefits of embryo pooling with PGT-A in improving pregnancy rates and reducing aneuploidy risk (46).

**Relation to Existing Literature:** Our findings are consistent with previous studies demonstrating the efficacy of PGT-A in reducing aneuploidy risk (47, 48). However, our study extends this research by providing personalized predictions for women over 40. Our results also complement studies on repeated cycles, highlighting the importance of considering individual patient characteristics when selecting a treatment approach (49, 50).

**Implications:** Our study's findings have significant implications for clinical practice. By providing personalized predictions, our models can inform treatment decisions for women over 40, potentially improving pregnancy rates and reducing aneuploidy risk. Our approach can also help clinicians counsel patients about their treatment options and expected outcomes (51).

**Limitations:** Our study relied on simulated data, which may not fully capture the complexities of real-world treatment outcomes. Additionally, our models made assumptions about treatment protocols and patient characteristics, which may not always be accurate (52). These performance metrics are based on simulated data and may not reflect real-world performance. Additionally, the refinement score is designed to be used in conjunction with the initial score, and its performance may be influenced by the quality of the initial score.

**Future Directions:** Future research should focus on validating our models using real-world data from fertility clinics. This will enable us to refine our approach, improve its accuracy, and explore its potential applications in clinical practice (1).

**Research Significance:** Our study contributes to the growing body of research on personalized medicine in reproductive health. By developing predictive models for embryo pooling with PGT-A versus repeated cycles, we provide a valuable tool for clinicians and patients navigating fertility treatment options (53).

## Conclusion:

AI-driven predictive modeling offers a novel, data-supported approach to personalized fertility care. These models facilitate evidence-based decision-making, potentially improving clinical outcomes. Further validation in real-world clinical settings is warranted.

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