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Artificial Intelligence in the IVF Laboratory: A Systematic Review and SWOT-Based Evaluation of Emerging Applications

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Abstract:
Background: Artificial intelligence (AI) has rapidly emerged as a transformative force in assisted reproductive technologies (ART), improving precision, objectivity, and reproducibility in laboratory workflows. From sperm and oocyte assessment to embryo grading and non-invasive genetic testing, AI-driven systems are redefining the embryology laboratory environment.
Objective: This review aims to systematically evaluate recent applications of AI in ART laboratories, identify methodological strengths and limitations, and provide a comprehensive SWOT-based analysis to guide future research and implementation.
Methods: A systematic search of PubMed, Scopus, and Web of Science databases was performed for studies published between 2020 and 2025. Inclusion criteria focused on original research and reviews investigating AI, machine learning (ML), or deep learning (DL) within laboratory aspects of ART. Extracted data were categorized by application area, including sperm analysis, oocyte evaluation, embryo viability prediction, non-invasive diagnostics, and laboratory automation.
Results: A total of 94 eligible studies were analyzed. Most employed DL and convolutional neural network (CNN) models for image-based assessment, achieving up to 97% accuracy in gamete and embryo evaluation. Approximately 25% integrated time-lapse imaging, and 15% combined AI with multi-omics or cfDNA-based diagnostics. The SWOT analysis revealed key strengths (accuracy, reproducibility, predictive power), weaknesses (data heterogeneity, cost, ethical concerns), opportunities (automation, personalized medicine, integration with robotics), and threats (data privacy, bias, regulatory gaps).
Conclusions: AI is not a replacement for human expertise but a powerful ally that enhances decision-making in ART laboratories. Standardized datasets, explainable algorithms, and ethical frameworks are essential for ensuring transparent, equitable, and clinically validated implementation of AI in reproductive medicine.

Keywords: Artificial intelligence; Machine learning; Assisted reproductive technology; Embryology; IVF laboratory; Deep learning; Non-invasive embryo testing.

Abbreviations: AI: Artificial intelligence; ML: Machine learning; DL: Deep learning; CNN: Convolutional neural network; SVM: Support vector machine; ART: Assisted reproductive technology; IVF: In vitro fertilization; ICSI: Intracytoplasmic sperm injection; TLS: Time-lapse systems; PGT-A: Preimplantation genetic testing for aneuploidy; QC: Quality control; ICM: Inner cell mass; TE: Trophectoderm.

Introduction

Effective solutions for the management of infertility. Despite continuous improvements in laboratory techniques, such as controlled ovarian stimulation, intracytoplasmic sperm injection (ICSI), and time-lapse embryo imaging, success rates of in vitro fertilization (IVF) remain suboptimal, with global live birth rates ranging between 30% and 40% per initiated cycle(1, 2). One of the major challenges in ART laboratories is the high degree of subjectivity in gamete and embryo evaluation, which depends largely on the experience and perception of embryologists. This subjectivity contributes to inter-observer variability, inconsistent grading, and unpredictable clinical outcomes (2).

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a transformative paradigm capable of overcoming these limitations. By analyzing complex datasets and extracting latent patterns beyond human perception, AI offers the potential to enhance decision-making accuracy, efficiency, and standardization in ART laboratories (3, 4)Over the last decade, AI has been increasingly applied across multiple stages of ART, including sperm selection, oocyte classification, embryo viability prediction, and implantation assessment (5, 6).

Recent studies have demonstrated the ability of convolutional neural networks (CNNs) to evaluate blastocyst morphology and predict implantation outcomes with higher reproducibility than manual scoring systems (7, 8). Moreover, deep learning–based non-invasive preimplantation genetic testing (niPGT) approaches using cell-free DNA (cfDNA) from spent culture media have introduced a paradigm shift toward safer and more efficient embryo

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selection(9). Similarly, AI-driven sperm analysis tools have improved assessment of motility and morphology, offering more objective and automated evaluation compared to traditional computer-assisted semen analysis (CASA) systems (10).

Beyond imaging and morphology, AI has also been integrated with multi-omics data, electronic medical records, and wearable sensors to predict treatment outcomes and personalize therapeutic strategies(11). These integrative frameworks are redefining precision medicine in reproductive healthcare. Nonetheless, challenges remain, including the need for standardized datasets, algorithm transparency, and ethical considerations surrounding patient privacy and clinical accountability (12).

Therefore, this review aims to provide a comprehensive overview of the emerging applications of artificial intelligence in assisted reproduction, with a specific focus on laboratory aspects. It discusses the recent technological advances, laboratory automation, and validation requirements while exploring the future directions toward fully digital and AI-empowered reproductive laboratories.

Methods

Review criteria: search strategy

This study was designed as a comprehensive narrative and semi-systematic review focusing on the laboratory applications of artificial intelligence (AI) within assisted reproductive technologies (ART). The methodological framework followed the recommendations for scoping reviews outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) (13). The objective was to identify, synthesize, and critically evaluate recent literature (2020–2025) addressing the implementation of machine learning, deep learning, and computational modeling in ART laboratory settings.

Literature Search Strategy

A structured literature search was conducted across three major scientific databases — PubMed, Scopus, and Web of Science — between January 2020 and February 2025. The following search terms and Boolean combinations were used :("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks") AND ("assisted reproduction" OR "IVF" OR "in vitro fertilization" OR "embryology" OR "embryo grading" OR "sperm analysis" OR "oocyte" OR "blastocyst"). Searches were limited to English-language articles published in peer-reviewed journals. Additional sources, including conference proceedings, preprints, and cross-referenced citations, were manually screened to ensure comprehensive coverage of the latest advances.

Studies were included if they met the following criteria: Focused on applications of AI, ML, or DL in ART laboratory procedures. Involved human or animal models relevant to reproductive medicine. Reported quantifiable laboratory or clinical outcomes (e.g., embryo viability, fertilization rate, implantation rate).Published between 2020 and 2025. Exclusion criteria included:

Non-English publications, editorials, and commentaries. Studies not related to laboratory or diagnostic aspects of ART. Duplicate or non-peer-reviewed reports.

Data Extraction and Synthesis

Two reviewers independently screened titles, abstracts, and full texts to ensure adherence to inclusion criteria. Extracted data included study design, AI methodology, dataset characteristics, validation strategies, and clinical outcomes. Discrepancies were resolved by consensus.

Data synthesis was performed using thematic analysis, categorizing studies into five major domains:

1) AI in sperm analysis and selection
2) AI in oocyte assessment
3) AI in embryo grading and viability prediction
4) AI in non-invasive genetic and metabolic assessment
5) AI in laboratory automation and quality control

The evidence was qualitatively summarized to identify patterns, trends, and gaps in current research.

Results

Overview of Included Studies

A total of 94 studies published between 2020 and 2025 were identified and analyzed after applying inclusion and exclusion criteria. Most of the included studies employed deep learning (DL) and convolutional neural network (CNN) models for embryo or sperm image interpretation, while others implemented machine learning (ML) approaches for predictive analytics and outcome optimization.

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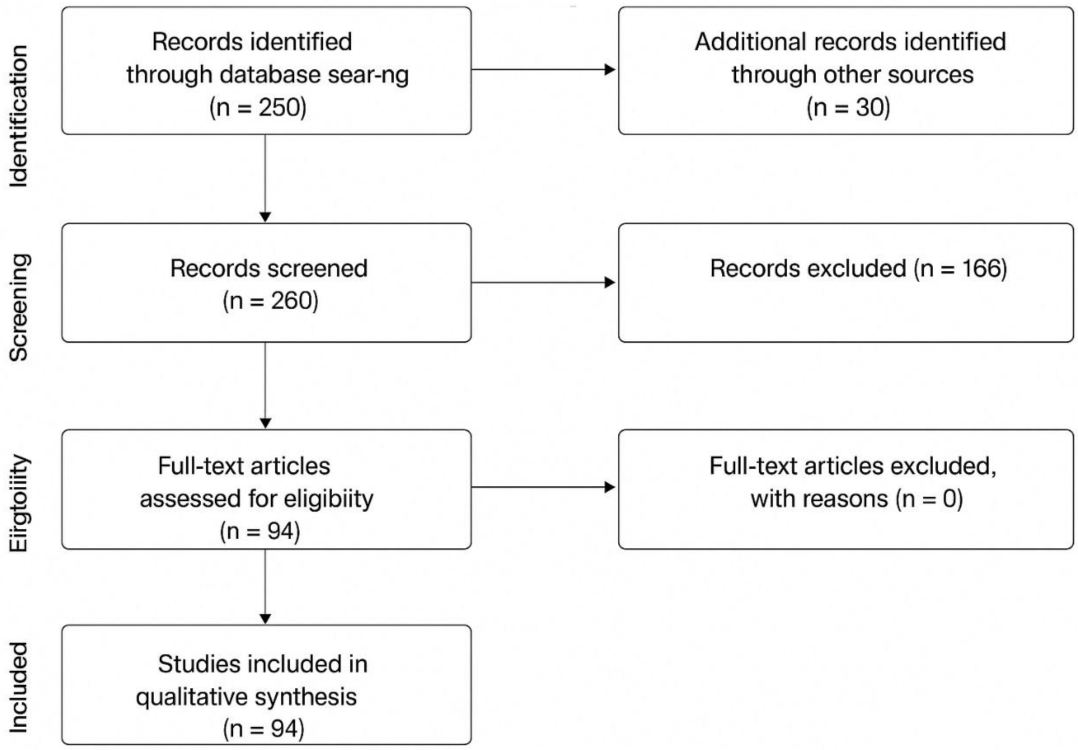

Figur.2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) workflow reporting the literature search strategy

Approximately 60% of the studies used retrospective datasets from IVF clinics, whereas 25% utilized time-lapse imaging systems, and 15% integrated multi-omics or cfDNA-based non-invasive diagnostics (14, 15). The included studies are categorized by their primary application area in Table 1, which provides a summary of key examples, the AI models employed, and their main reported outcomes.

Table 1: Studies included in this systematic review, categorized by primary application area

Primary Application Area	Key Examples of AI Models / Systems	Main Reported Outcomes	Grade of Evidence[a]	Reference Numbers
AI in Sperm Selection and Analysis	CNN-based CASA, ML-microfluidic integration	Accuracy up to 97% in morphology classification; improved sperm recovery rates; reduced DNA fragmentation	IIa	(16-23)
AI in Oocyte Evaluation	DL for polar body & spindle imaging; ML with transcriptomic data	Improved maturity & quality classification; enhanced fertilization prediction	IIb	(24-29)
AI in Embryo Grading and Viability Prediction	iDAScore, KIDScore, STORK, GANs for data augmentation	Implantation prediction accuracy 80-90%;	Ia	(30-41)

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		improved euploidy prediction (AUC >0.92)		
AI in Non-Invasive Genetic and Metabolic Testing	ML for cfDNA fragmentomics; Raman spectroscopy AI	>85% sensitivity in aneuploidy detection; non-invasive metabolic monitoring	IIa	(42-52)
AI in Laboratory Automation and Quality Control	AI-guided robotics for ICSI; predictive maintenance algorithms	Submicron precision in manipulation; real-time environmental monitoring	III	(53-61)

[a]Grade of Evidence Legend (Adapted from Oxford Centre for Evidence-Based Medicine Levels):

- **Ia:** Evidence from meta-analysis of high-quality, randomized controlled trials.
- **IIa:** Evidence from at least one well-designed controlled study without randomization.
- **IIb:** Evidence from at least one other type of well-designed quasi-experimental study.
- **III:** Evidence from well-designed non-experimental descriptive studies, such as comparative studies, correlation studies, or case-control studies.

AI in Sperm Selection and Analysis

AI-based sperm assessment has markedly enhanced the precision and reproducibility of semen evaluation, overcoming the inherent subjectivity associated with manual microscopic grading. Traditional computer-aided sperm analysis (CASA) systems are limited by threshold-dependent algorithms that cannot adapt to morphological variability across patients or laboratories. In contrast, deep learning–assisted CASA platforms utilize convolutional neural networks (CNNs) to automatically extract complex spatial features from thousands of sperm images, enabling accurate classification of motility patterns, head morphology, midpiece integrity, and tail abnormalities (16, 17).

Recent studies report that AI-enhanced CASA systems achieved up to 95–97% accuracy in distinguishing morphologically normal spermatozoa from abnormal ones-significantly higher than traditional manual or semi-automated methods (18, 19). Such systems also demonstrated higher intra- and inter-observer consistency, reducing analytical bias in fertility assessments.

The integration of machine learning (ML) with microfluidic sperm-sorting devices represents another important advancement. Microfluidics, which mimics the physiological microenvironment of the female reproductive tract, can be optimized using ML algorithms to dynamically adjust flow parameters and selection thresholds. Studies have shown that AI-driven microfluidic systems improved sperm recovery rates, reduced DNA fragmentation, and shortened processing times by more than 40% compared with conventional density-gradient centrifugation(18, 20).These technologies collectively improve selection of high-quality, motile spermatozoa while minimizing oxidative stress and mechanical damage-factors crucial for subsequent fertilization and embryo development(21).

Furthermore, AI models have been trained to predict fertilization outcomes based on integrated sperm motility, morphokinetic trajectories, and genetic integrity data, offering predictive insights into sperm performance before insemination. This predictive capability supports personalized ART protocols and potentially enhances fertilization and live birth rates (22, 23).

AI in Oocyte Evaluation

Accurate evaluation of oocyte quality is pivotal for predicting fertilization success and embryonic development. Conventional morphological assessment remains subjective and limited to visual inspection under polarized or light microscopy. AI and DL technologies have addressed this limitation by introducing

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objective, quantifiable models (24, 25). AI in Oocyte Evaluation (6, 26).

In addition, ML algorithms integrating transcriptomic data from cumulus and granulosa cells-alongside patient age, BMI, and hormonal profiles-have enhanced the accuracy of predicting oocyte retrieval and fertilization outcomes(27).These multimodal models provide deeper biological context by linking visual and molecular signatures of oocyte quality.

Notably, explainable AI (XAI) models are emerging to improve interpretability by visualizing feature maps responsible for oocyte classification. Such explainable frameworks could facilitate regulatory acceptance and clinical trust by enabling embryologists to understand algorithmic reasoning (28, 29).

AI in Embryo Grading and Viability Prediction

Embryo evaluation is a cornerstone of ART laboratory decision-making, yet remains highly dependent on subjective human judgment. The introduction of AI-driven embryo grading systems has transformed this process, enhancing consistency and predictive power (30). Deep learning models such as iDAScore, KIDScore, and STORK analyze time-lapse images to quantify morphokinetic features—cell division timing, fragmentation dynamics, blastocyst expansion, and trophectoderm morphology—providing implantation predictions with 80–90% accuracy, surpassing manual grading(٣٣-٣١).

Generative AI, particularly Generative Adversarial Networks (GANs), has recently been applied to augment embryo datasets by generating realistic synthetic images. These expanded datasets enable better model generalization and reduce overfitting in data-limited environments(٣٦-٣٤).

Moreover, hybrid models combining morphokinetic and metabolomic data have demonstrated improved prediction of euploidy and live birth potential. For example, AI-based morphokinetic–metabolomic integrators achieved AUC > 0.92 for euploid embryo prediction, highlighting the translational potential of multi-parameter AI frameworks (6, 37, 38).

Importantly, the goal is not to replace embryologists but to create decision-support systems that enhance reproducibility, minimize bias, and provide real-time feedback during embryo selection. Ongoing clinical validation studies are assessing the utility of these tools for improving pregnancy and live birth rates (39-41).

AI in Non-Invasive Genetic and Metabolic Testing

Non-invasive preimplantation genetic testing (niPGT) has gained momentum as an alternative to trophectoderm biopsy, reducing potential harm to embryos. AI-assisted analysis of cell-free DNA (cfDNA) and spent culture media allows reliable chromosomal and metabolic assessment without physical intervention (42, 43). Machine learning models trained on cfDNA fragmentomics, methylation profiles, and secretome data have achieved sensitivity exceeding 85% in detecting aneuploid embryos (44-46) .Integration of proteomic and metabolomic markers further improves embryo viability prediction, allowing stratification of embryos based on implantation potential(٤٨ ,٤٧). AI algorithms are also being applied to mass spectrometry and Raman spectroscopy data from embryo culture media to detect biochemical changes linked to metabolic activity. These models provide continuous, label-free embryo monitoring, promoting safer and more informed selection (49, 50). However, despite promising performance, niPGT algorithms require large-scale multicenter validation and standardization before clinical deployment (51, 52).

AI in Laboratory Automation and Quality Control

AI, coupled with robotics and Internet of Things (IoT) technology, is driving the automation of ART laboratories, improving precision and reducing human error. Automated micromanipulation systems guided by AI vision algorithms have achieved submicron precision in handling gametes and embryos during ICSI and biopsy procedures(٥٤ ,٥٣). Robotic arms integrated with vision-based AI can identify oocytes, inject sperm, and transfer embryos autonomously while maintaining high consistency in success rates(55).

Furthermore, predictive maintenance algorithms are being deployed for incubators and culture systems, enabling real-time monitoring of temperature, pH, and gas composition. By applying anomaly-detection ML models, laboratories can detect early deviations and prevent equipment failures (٥٧ ,٥٦).These systems also generate large volumes of operational data, which can be used to continuously optimize environmental conditions for embryo development(58, 59). AI-based

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quality control systems use historical outcome data to identify laboratory workflow bottlenecks and performance trends, facilitating continuous process improvement and compliance with accreditation standards (60, 61). Collectively, these advancements are paving the way toward “smart laboratories”, where automation, robotics, and machine intelligence harmoniously collaborate to enhance laboratory reliability, safety, and efficiency(58).

Table2. “Overview of Machine Learning and Deep Learning Models in ART”

Enhancing Accuracy and Reproducibility

One of the most consistent findings across recent studies is that AI significantly reduces inter- and intra-observer variability, addressing a long-standing limitation in ART laboratories (35, 62), Traditional grading of gametes and embryos is highly dependent on the subjective experience of embryologists, leading to inconsistent interpretations and variable clinical outcomes. AI-based tools such as deep learning–assisted CASA systems and CNN-based embryo scoring models provide reproducible and quantifiable assessments that outperform manual approaches in predictive accuracy (7, 63).

The incorporation of large-scale imaging and time-lapse datasets has allowed these systems to recognize subtle morphological and morphokinetic markers correlated with developmental competence, euploidy, and implantation success. As a result, AI enhances reproducibility while offering clinician’s objective, evidence-based parameters to support embryo and gamete selection.

Translational Potential and Clinical Benefits

AI-based decision-support systems are not designed to replace embryologists but rather to augment their analytical capacity. Clinical studies indicate that AI-assisted embryo selection correlates with improved implantation and ongoing pregnancy rates, particularly when combined with time-lapse imaging and morphokinetic analysis (6, 64).

Similarly, deep learning–based sperm and oocyte evaluation systems provide early, accurate, and standardized data that allow for better timing of fertilization and embryo transfer (65, 66).

Beyond improving laboratory precision, AI also supports personalized reproductive medicine by integrating multi-omics and clinical data. Machine learning models that consider patient-specific features-such as age, BMI, hormonal profile, and genetic background-can tailor stimulation protocols and optimize embryo transfer strategies, thereby improving success rates and reducing the physical and emotional burden of repeated IVF cycles (67-69).

Integration with Robotics, Automation, and Multi-Omics

The fusion of AI with robotics and automation heralds the era of the “intelligent laboratory.” AI-driven micromanipulation systems have already demonstrated precise control in ICSI and embryo biopsy procedures, reducing human dependency and operator-induced errors (70, 71).

Predictive maintenance algorithms further enhance laboratory stability by continuously monitoring incubator conditions and preventing fluctuations detrimental to embryo culture(58).

Simultaneously, integration of AI with multi-omics datasets-including transcriptomic, proteomic, and metabolomic data-offers deeper insight into gamete and embryo physiology(72). Such integrative approaches are paving the way toward systems-level reproductive biology, where AI correlates molecular and phenotypic profiles to predict developmental potential with unprecedented precision (73).

Ethical, Regulatory, and Practical Considerations

Despite its promise, the implementation of AI in ART laboratories introduces ethical and regulatory challenges (74). Data privacy and algorithmic transparency remain major concerns, particularly given the sensitive nature of reproductive data. The “black-box” nature of deep neural networks makes it difficult for clinicians to interpret model decisions and ensure accountability(40).

Efforts to address these issues include the development of explainable AI (XAI) frameworks, which provide visual maps or interpretable decision pathways, increasing clinician confidence and patient trust (75). Regulatory agencies and professional societies must also define standardized validation protocols, ensuring that AI systems are clinically safe, unbiased, and generalizable across diverse populations(76).

The landscape of reproductive medicine. From sperm and oocyte evaluation to embryo grading, non-invasive genetic testing, and laboratory automation, AI-driven systems are enhancing precision, objectivity, and efficiency in every stage of the reproductive process. The

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convergence of computer vision, deep learning (DL), and predictive analytics has enabled the extraction of clinically meaningful patterns from large and complex datasets, improving embryo selection accuracy, standardizing laboratory workflows, and potentially increasing implantation and live birth rates(77, 78).

Table2. "Overview of Machine Learning and Deep Learning Models in ART"

Stage	ML/DL Model	Application	Brief Description	Input Data Type
Sperm Analysis	CNN	Sperm morphology assessment	Extract complex visual features from sperm images	Microscopic images
	Classical ML (SVM, Random Forest, XGBoost)	Predict sperm quality	Analyze morphologic and motility features	Numerical & analytical features
	GAN	Dataset augmentation	Generate synthetic sperm images to prevent overfitting	Images
	LSTM / RNN	Sperm trajectory prediction	Analyze temporal motion sequences of sperm	Time-series / spatiotemporal data
Oocyte Evaluation	CNN	Maturity & quality detection	Analyze microscopic images of oocytes and polar body	Images
	Classical ML (SVM, Random Forest)	Predict fertilization success	Combine image features with patient clinical parameters	Images + clinical data
	Ensemble Models	Improve prediction accuracy	Combine multiple models to reduce error	Images + clinical data
	Explainable AI (XAI)	Model decision transparency	Highlight important features influencing oocyte quality	Images
Embryo Grading & Viability	CNN	Blastocyst image assessment	Predict embryo quality and implantation potential	Time-lapse images
	LSTM / RNN	Embryo time-lapse growth analysis	Predict development based on sequential images	Sequential images
	GAN	Synthetic embryo data	Generate synthetic images to augment datasets	Images
	Hybrid Models (CNN + ML)	Predict euploidy & live birth rates	Combine morphology and multi-omics data	Images + multi-omics data
Non-invasive Genetic & Metabolic Testing	ML (Random Forest, XGBoost)	Predict aneuploidy	Analyze cfDNA, proteomics, and metabolomics	Molecular data
	CNN	Culture media image analysis	Detect metabolic and health changes in embryos	Images
	Autoencoder	Dimensionality reduction & pattern discovery	Extract hidden features from molecular datasets	Multi-omics data
Lab Automation & QC	CNN + Vision-based AI	Robotic ICSI & biopsy guidance	Automated detection of oocytes & sperm, robot assistance	Images
	ML (Anomaly Detection)	Predict equipment failure	Monitor incubator & equipment parameters	Sensor data
	Reinforcement Learning	Optimize lab conditions	Learn policies for optimal environmental control	Environmental & outcome data
	Predictive Models	Workflow optimization	Predict errors and improve quality control	Operational & outcome data

Limitations

Despite its transformative potential, several limitations constrain the current use of AI in ART. First, the lack of standardized datasets and image acquisition protocols hampers reproducibility across centers and populations. Most available datasets are

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retrospective, limited in sample diversity, and proprietary, restricting transparency and algorithmic benchmarking(79, 80).

Second, data privacy and algorithmic bias remain key concerns. Deep learning systems often operate as "black boxes," making it difficult to interpret or audit their decision processes, which can limit clinical trust and regulatory approval. Third, AI applications are frequently tested on small, homogeneous datasets, limiting generalizability and real-world applicability(81).

In addition, the integration of AI into ART laboratories requires substantial infrastructure investment, including data management systems, computational resources, and personnel training. These barriers can delay adoption, particularly in low-resource clinical settings. Finally, the ethical implications-such as patient consent, data ownership, and accountability for AI-driven recommendations-must be carefully addressed before large-scale deployment(82).

Future Directions

Future research must focus on building multicenter, standardized, and open-access datasets that enable transparent and reproducible AI development(83). Collaborative consortia between fertility clinics, academic institutions, and AI developers will be crucial for ensuring data harmonization and model generalizability(84).

The next generation of AI tools should prioritize explainability, fairness, and interoperability, aligning with the principles of responsible AI. Hybrid systems that integrate robotics, multi-omics profiling, and digital twins could provide real-time simulation and optimization of laboratory conditions, advancing the vision of a fully automated, intelligent ART laboratory(85).

Additionally, AI's potential to guide non-invasive embryo selection and personalized treatment planning should be explored through prospective, randomized clinical trials. Integration with wearable biosensors and telemedicine platforms could expand reproductive monitoring beyond laboratory boundaries, enhancing continuity of care(86) .

Finally, international regulatory bodies and scientific societies should develop unified frameworks for algorithm validation, quality assurance, and ethical governance. Only through these concerted efforts can AI truly fulfill its promise of reshaping reproductive healthcare—transforming ART from a procedure of probability into a science of precision.Discussion:

The integration of artificial intelligence (AI) into assisted reproductive technologies (ART) represents a transformative leap toward objective, data-driven laboratory medicine. By uniting computational science and embryology, AI offers new perspectives for understanding gamete and embryo biology, optimizing laboratory workflows, and improving clinical outcomes. This review highlights how recent AI-driven innovations—ranging from sperm assessment to non-invasive embryo testing—are reshaping the operational and analytical landscape of ART laboratories.

Strengths-weaknesses-opportunitiesthreats (SWOT) analysis

A SWOT analysis has been conducted to assess the available evidence linking the artificial intelligence in ART Laboratories (Fig.2) rengths-weaknesses-opportunitiesthreats (SWOT) analysis:

Strengths (Internal, positive factors)

- Enhanced Accuracy and Objectivity: Reduces reliance on subjective embryologist assessment and minimizes human error in selecting sperm, oocytes, and embryos.
- Superior Predictive Power: Utilizes predictive models based on morphokinetic and multi-omics data to improve implantation and live birth rates.
- Laboratory Process Automation: Integrates with robotics to perform sensitive procedures like ICSI and embryo biopsy with high, sub-micron precision.
- Improved Quality Control (QC) and Maintenance: Employs predictive algorithms to monitor incubator conditions in real-time, preventing detrimental environmental fluctuations.
- Increased Reproducibility: Significantly reduces inter- and intra-observer variability, standardizing assessments across the laboratory.

Weaknesses (Internal, negative factors)

- Limited Standardized Datasets: A lack of unified data acquisition protocols and limited demographic diversity in datasets hinder reproducibility and generalizability.
- "Black-Box" Nature of Models: The lack of transparency in complex AI decision-making processes can erode clinical trust and complicate accountability.
- High Implementation Costs: Significant investment is required for computational infrastructure, data storage systems, and specialized staff training.
- Ethical and Regulatory Hurdles: Unresolved concerns regarding patient data privacy, data ownership, and liability for AI-driven clinical recommendations.

Opportunities (External, positive factors)

- Integration with Multi-Omics Data: Combining genomic, transcriptomic, and metabolomic data to create more accurate, holistic predictive models of embryo viability.

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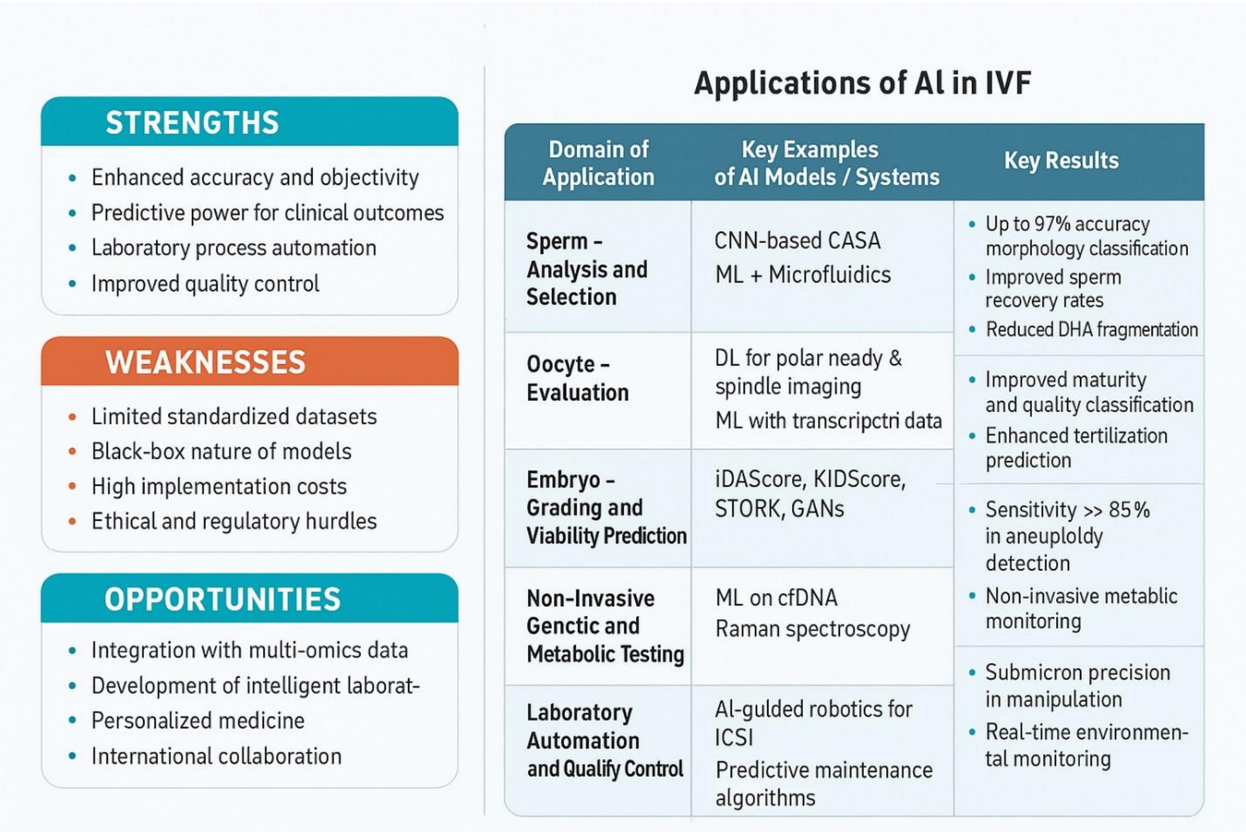
- Development of Fully Intelligent Laboratories: Creating integrated ecosystems that leverage AI, robotics, and the Internet of Things (IoT) to create fully optimized, automated workflows.
- Advancement of Personalized Medicine: Tailoring stimulation protocols and embryo transfer strategies based on individual patient clinical, molecular, and genetic profiles.
- International Collaboration and Consortia: Forming multicenter partnerships to develop large-scale, standardized, and diverse datasets for building robust and generalizable models.

Threats (External, negative factors)

- Data Security and Privacy Risks: Potential for misuse of highly sensitive reproductive and genetic data, alongside challenges in ensuring truly informed consent for data usage.
- Algorithmic Bias: Models trained on limited, imbalanced, or non-diverse datasets may perpetuate or even amplify biases, leading to poor performance when applied to broader populations.
- Regulatory and Validation Challenges: The absence of universally accepted frameworks for the clinical validation, certification, and ongoing monitoring of AI algorithms in ART.
- Resistance to Adoption: Reluctance among clinicians and embryologists to adopt and trust AI systems due to a lack of explainability, insufficient training, or concerns about job displacement.

1. Fig. 2. Strengths-Weaknesses-Opportunities-Threats (SWOT) analysis has been conducted to define AI in ART laboratories



Conclusion

The rapid evolution of artificial intelligence (AI) in assisted reproductive technologies (ART) has redefined the landscape of reproductive medicine (87). From sperm and oocyte evaluation to embryo grading, non-invasive genetic testing, and laboratory automation, AI-driven systems are enhancing precision, objectivity, and efficiency in every stage of the reproductive process (88). The convergence of computer vision, deep learning (DL), and predictive analytics has enabled the extraction of clinically meaningful patterns from large and complex datasets, improving embryo selection accuracy, standardizing laboratory workflows, and potentially increasing implantation and live birth rates(89, 90).AI is not a replacement for human expertise but a powerful ally that augments the capabilities of embryologists and clinicians. By reducing subjectivity, minimizing inter-observer variability, and generating evidence-based recommendations (91, 92), AI promotes consistency and transparency in laboratory decision-making. Its role extends beyond image analysis to integrative prediction models that combine multi-omics, cfDNA, and patient clinical data, paving the way for personalized and precision reproductive medicine (93, 94).As these technologies mature, the clinical translation of AI in ART will depend on rigorous validation, ethical oversight, and cross-disciplinary collaboration (92). The successful integration of AI will ultimately transform reproductive laboratories into intelligent ecosystems capable of adaptive learning, continuous quality improvement, and enhanced patient outcomes.

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Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

All data supporting the findings of this review are derived from publicly available sources cited within the manuscript. Additional data or materials related to this study can be made available by the corresponding author upon reasonable request.

Author Contributions

Fatemeh Dehghanpour conceptualized the study, conducted the literature review, performed the data analysis and interpretation, and drafted and critically revised the manuscript. The author approved the final version for submission and agrees to be accountable for all aspects of the work.

References:

1. Jiang Y, Yuan JC, Song G, Zhang XH, Miao SB, Wu XH. Comparing the pregnancy outcomes of Re-ICSI and ICSI embryos in fresh ET and FET cycles. Biomedical reports. 2023;19(4):66.
2. Choudhary A, Choudhary DS, Ghatak S. Estimation of Fertilization Rate, Implantation Rate, Pregnancy Rate and Live Birth Rate in Intracytoplasmic Sperm Injection in Association with Number of Attempts and Sperm Morphology. Mymensingh medical journal : MMJ. 2021;30(2):531-7.
3. Gill ME, Quaas AM. Looking with new eyes: advanced microscopy and artificial intelligence in reproductive medicine. J Assist Reprod Genet. 2023;40(2):235-9.
4. Hew Y, Kutuk D, Duzcu T, Ergun Y, Basar M. Artificial Intelligence in IVF Laboratories: Elevating Outcomes Through Precision and Efficiency. Biology. 2024;13(12).
5. Jiang VS, Bormann CL. Artificial intelligence in the in vitro fertilization laboratory: a review of advancements over the last decade. Fertility and sterility. 2023;120(1):17-23.
6. Olawade DB, Teke J, Adeleye KK, Weerasinghe K, Maidoki M, Clement David-Olawade A. Artificial intelligence in in-vitro fertilization (IVF): A new era of precision and personalization in fertility treatments. Journal of gynecology obstetrics and human reproduction. 2025;54(3):102903.
7. Isa IS, Yusof UK, Mohd Zain M. Image processing approach for grading IVF blastocyst: A state-of-the-art review and future perspective of deep learning-based models. Applied Sciences. 2023;13(2):1195.
8. Bormann CL, Kanakasabapathy MK, Thirumalaraju P, Gupta R, Pooniwala R, Kandula H, et al. Performance of a deep learning based neural network in the selection of human blastocysts for implantation. elife. 2020;9:e55301.
9. Zhou Q, Wang Y. Noninvasive Testing of Preimplantation Embryos in Assisted Reproductive Technology. New Perspectives in Human Embryology: IntechOpen; 2024.
10. Furini C, Costantino F, Granata AR, Spaggiari G, Santi D, Simoni M. Still counting sperm? Why novel, truly informative measurements of testis function in male infertility are urgently needed. Endocrine. 2025:1-12.

International Journal of Psychology , Social and Educational Sciences
Vol.6, NO.3 , P: 79-92
Received: 10 April 2025
Accepted: 20 January 2026

11. Ali H. Artificial intelligence in multi-omics data integration: Advancing precision medicine, biomarker discovery and genomic-driven disease interventions. Int J Sci Res Arch. 2023;8(1):1012-30.
12. Suura SR. Integrating Artificial Intelligence, Machine Learning, and Big Data with Genetic Testing and Genomic Medicine to Enable Earlier, Personalized Health Interventions: Deep Science Publishing; 2025.
13. Page O. Preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) checklist. Br J Sports Med. 2024;1001:58.
14. Samura O, Okamoto A. Causes of aberrant non-invasive prenatal testing for aneuploidy: A systematic review. Taiwanese journal of obstetrics & gynecology. 2020;59(1):16-20.
15. Liu L, Liang H, Yang J, Shen F, Chen J, Ao L. Clinical data-based modeling of IVF live birth outcome and its application. Reproductive biology and endocrinology. 2024;22(1):76.
16. Abou Ghayda R, Cannarella R, Calogero AE, Shah R, Rambhatla A, Zohdy W, et al. Artificial intelligence in andrology: from semen analysis to image diagnostics. The world journal of men's health. 2023;42(1):39.
17. Cherouveim P, Velmahos C, Bormann CL. Artificial intelligence for sperm selection—A systematic review. Fertility and sterility. 2023;120(1):24-31.
18. Baldán FJ, García-Gil D, Fernandez-Basso C. Revolutionizing Sperm Analysis with AI: A Review of Computer-Aided Sperm Analysis Systems. Computation. 2025;13(6):132.
19. Kikuchi J, Lorimer J, Shahali S, Nosrati R. Artificial intelligence for semen analysis and sperm selection. Robotics and Artificial Intelligence for Reproductive Medicine: Elsevier; 2026. p. 133-60.
20. Amini Mahabadi J, Enderami SE, Nikzad H, Hassani Bafrani H. The Use of Machine Learning for Human Sperm and Oocyte Selection and Success Rate in IVF Methods. Andrologia. 2024;2024(1):8165541.
21. Huang TK, Huang CH, Chen PA, Chen CH, Lu F, Yang WJ, et al. Development of a thermotaxis and rheotaxis microfluidic device for motile spermatozoa sorting. Biosensors & bioelectronics. 2024;258:116353.
22. Hynniewta BC, Navas F, Marbaniang K. Artificial intelligence in assisted reproduction: the future for reproductive medicine. International Journal of Reproduction, Contraception, Obstetrics and Gynecology.14(9):3182.
23. Anbari F, Khalili MA, Sultan Ahamed AM, Mangoli E, Nabi A, Dehghanpour F, et al. Microfluidic sperm selection yields higher sperm quality compared to conventional method in ICSI program: A pilot study. Systems biology in reproductive medicine. 2021;67(2):137-43.
24. Raes A, Babin D, Pascottini OB, Opsomer G, Van Soom A, Smits K. Artificial intelligence outperforms humans in morphology-based oocyte selection in cattle. Sci Rep. 2025;15(1):21829.
25. Medenica S, Zivanovic D, Batkoska L, Marinelli S, Basile G, Perino A, et al. The Future Is Coming: Artificial Intelligence in the Treatment of Infertility Could Improve Assisted Reproduction Outcomes-The Value of Regulatory Frameworks. Diagnostics (Basel, Switzerland). 2022;12(12).
26. Saffari H, Fathi D, Palay P, Gourabi H, Fathi R. Machine learning and microfluidic integration for oocyte quality prediction. Scientific Reports. 2025;15(1):26532.
27. Chen F, Chen Y, Mai Q. Multi-Omics Analysis and Machine Learning Prediction Model for Pregnancy Outcomes After Intracytoplasmic Sperm Injection–in vitro Fertilization. Frontiers in Public Health. 2022;10:924539.
28. Mohsin Khan M, Shah N, Shaikh N, Thabet A, Alrabayah T, Belkhair S. Towards secure and trusted AI in healthcare: A systematic review of emerging innovations and ethical challenges. International journal of medical informatics. 2025;195:105780.
29. Khani M, Luo J, Assadi Shalmani M, Taleban A, Adams J, Friedland DR. Advancing personalized healthcare: leveraging explainable AI for BPPV risk assessment. Health information science and systems. 2025;13(1):1.
30. Dhamija P, More A, Choudhary N, Wadhe T, Shah DR. Study Protocol: Evaluation of AI-Driven Grading Compared to Manual Grading in Predicting Embryo Viability and Successful Implantation and Clinical Pregnancy Outcomes in IVF Using Static Microscopic Images. Journal of pharmacy & bioallied sciences. 2025;17(Suppl 1):S956-s9.
31. Theilgaard Lassen J, Fly Kragh M, Rimestad J, Nygård Johansen M, Berntsen J. Development and validation of deep learning based embryo selection across multiple days of transfer. Scientific reports. 2023;13(1):4235.
32. Jiang VS, Bormann CL. Noninvasive genetic screening: current advances in artificial intelligence for embryo ploidy prediction. Fertility and sterility. 2023;120(2):228-34.
33. Jiang VS, Bormann CL. Noninvasive genetic screening: current advances in artificial intelligence for embryo ploidy prediction. Fertility and sterility. 2023;120(2):228-34.
34. da Silva JLR. Generative AI as surrogate models for superresolution fluid flow simulations. 2025.
35. Paya Bosch E. Deep learning for the automation of embryo selection in an in vitro fertilization laboratory. 2024.
36. Sun L, Li J, Zeng S, Luo Q, Miao H, Liang Y, et al. Artificial intelligence system for outcome evaluations of human in vitro fertilization-derived

embryos. Chinese medical journal. 2024;137(16):1939-49.
37. Pinto S, Guerra-Carvalho B, Crisóstomo L, Rocha A, Barros A, Alves MG, et al. Metabolomics integration in assisted reproductive technologies for enhanced embryo selection beyond morphokinetic analysis. International Journal of Molecular Sciences. 2023;25(1):491.
38. Ramanathan J. A Comparison Study between Machine Learning and Conventional Methods in Successful Embryo Identification Used in Assisted Reproductive Technologies: A Systematic Review and Meta-analysis: University of Bridgeport; 2021.
39. Canosa S. Novel strategies to improve human embryo selection in IVF: from morphokinetic analysis to Artificial Intelligence. 2021.
40. Tamir S. Artificial intelligence in human reproduction: Charting the ethical debate over AI in IVF. AI and Ethics. 2023;3(3):947-61.
41. Loewke K, Cho JH, Brumar CD, Maeder-York P, Barash O, Malmsten JE, et al. Characterization of an artificial intelligence model for ranking static images of blastocyst stage embryos. Fertility and sterility. 2022;117(3):528-35.
42. Makhijani R, Bartels CB, Godiwala P, Bartolucci A, DiLuigi A, Nulsen J, et al. Impact of trophectoderm biopsy on obstetric and perinatal outcomes following frozen–thawed embryo transfer cycles. Human reproduction. 2021;36(2):340-8.
43. Munné S, Horcajadas JA, Seth-Smith ML, Perugini M, Griffin DK. Non-invasive selection for euploid embryos: prospects and pitfalls of the three most promising approaches. Reprod Biomed Online. 2025;51(5):105077.
44. Bakalova DN, Navarro-Sánchez L, Rubio C. Non-Invasive Preimplantation Genetic Testing. Genes. 2025;16(5):552.
45. Voros C, Darlas M, Athanasiou D, Athanasiou A, Athanasiou A, Bananis K, et al. Evaluation of the Effectiveness and Accuracy of Non-Invasive Preimplantation Genetic Testing (niPGT) Compared to Invasive Embryo Biopsy. Biomedicines. 2025;13(8).
46. Volovsky M, Scott RT, Jr., Seli E. Non-invasive preimplantation genetic testing for aneuploidy: is the promise real? Human reproduction (Oxford, England). 2024;39(9):1899-908.
47. Ducreux B, Patrat C, Trasler J, Fauque P. Transcriptomic integrity of human oocytes used in ARTs: technical and intrinsic factor effects. Human reproduction update. 2024;30(1):26-47.
48. Hernández-Vargas P, Muñoz M, Domínguez F. Identifying biomarkers for predicting successful embryo implantation: applying single to multi-OMICs to improve reproductive outcomes. Human reproduction update. 2020;26(2):264-301.
49. Zmuidinaite R, Sharara FI, Iles RK. Current advancements in noninvasive profiling of the embryo culture media secretome. International Journal of Molecular Sciences. 2021;22(5):2513.
50. Sonehara H, Matsumoto R, Nakayama N, Kobanawa M, Numata K, Kawasaki A, et al. Aneuploidy and sex concordance rate between cell-free DNA analysis from spent culture media of preimplantation embryo and DNA from whole embryo with respect to different morphological grading. Reproductive medicine and biology. 2022;21(1):e12493.
51. Tsui WA, Ding SC, Jiang P, Lo YD. Artificial intelligence and machine learning in cell-free-DNA-based diagnostics. Genome Research. 2025;35(1):1-19.
52. Xie P, Zhang S, Gu Y, Jiang B, Hu L, Tan YQ, et al. Non-invasive preimplantation genetic testing for conventional IVF blastocysts. Journal of translational medicine. 2022;20(1):396.
53. Dimitriadis I, Zaninovic N, Badiola AC, Bormann CL. Artificial intelligence in the embryology laboratory: a review. Reproductive biomedicine online. 2022;44(3):435-48.
54. Al Shahrani AM, Alomar MA, Alqahtani KN, Basingab MS, Sharma B, Rizwan A. Machine Learning-Enabled Smart Industrial Automation Systems Using Internet of Things. Sensors (Basel, Switzerland). 2022;23(1).
55. Joshi AS, Alegria AD, Auch B, Khosla K, Mendana JB, Liu K, et al. Multiscale, multi-perspective imaging assisted robotic microinjection of 3D biological structures. Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual International Conference. 2021;2021:4844-50.
56. Ahmad I. Advances in Machine Learning for Monitoring, Control, and Optimization of Temperature of Reactors. 2023.
57. More D, Khan N, Tekade RK, Sengupta P. An Update on Current Trend in Sample Preparation Automation in Bioanalysis: strategies, Challenges and Future Direction. Critical reviews in analytical chemistry. 2025;55(7):1461-85.
58. Hew Y, Kutuk D, Duzcu T, Ergun Y, Basar M. Artificial Intelligence in IVF Laboratories: Elevating Outcomes Through Precision and Efficiency. Biology. 2024;13(12):988.
59. Si K, Huang B, Jin L. Application of artificial intelligence in gametes and embryos selection. Human fertility (Cambridge, England). 2023;26(4):757-77.
60. Doultani S, Sharma P, Makwana P, Patil S, Layek S, George L, et al. AI in Reproductive Biology: Transforming Fertility Assessment, ART, and Research. Annual Research & Review in Biology. 2024;39(9):147-58.
61. Ortiz-Escribano N, Bogado Pascottini O, Woelders H, Vandenberghe L, De Schauwer C, Govaere J, et al. An improved vitrification protocol for

equine immature oocytes, resulting in a first live foal. Equine veterinary journal. 2018;50(3):391-7.
62. Valera MA, Aparicio-Ruiz B, Pérez-Albalá S, Romany L, Remohí J, Meseguer M. Clinical validation of an automatic classification algorithm applied on cleavage stage embryos: analysis for blastulation, euploidy, implantation, and live-birth potential. Human reproduction (Oxford, England). 2023;38(6):1060-75.
63. Yuan Z, Yuan M, Song X, Huang X, Yan W. Development of an artificial intelligence based model for predicting the euploidy of blastocysts in PGT-A treatments. Sci Rep. 2023;13(1):2322.
64. Salih M, Austin C, Warty R, Tiktin C, Rolnik D, Momeni M, et al. Embryo selection through artificial intelligence versus embryologists: a systematic review. Human Reproduction Open. 2023;2023(3):hoad031.
65. Ouyang X, Wei J. Multi-Modal Artificial Intelligence of Embryo Grading and Pregnancy Prediction in Assisted Reproductive Technology: A Review. arXiv preprint arXiv:250520306. 2025.
66. Thompson HJ. Investigation of Plastic Lab Consumables and Their Impact on Sperm Viability: The University of Utah; 2025.
67. Bachelot G, Lévy R, Bachelot A, Faure C, Czernichow S, Dupont C, et al. Proof of concept and development of a couple-based machine learning model to stratify infertile patients with idiopathic infertility. Scientific Reports. 2021;11(1):24003.
68. Shufaro Y, Cohen M, Wertheimer A, Altman E, Wolff L, Sapir O, et al. Monitoring Ovarian Stimulation for Assisted Reproduction With Patient Self-Scans Using a Home Vaginal Ultrasound Device: A Single-Center Interventional, Prospective Study. Journal of Medical Internet Research. 2025;27:e72607.
69. Siristatidis C, Stavros S, Drakeley A, Bettocchi S, Pouliakis A, Drakakis P, et al. Omics and Artificial Intelligence to Improve In Vitro Fertilization (IVF) Success: A Proposed Protocol. Diagnostics (Basel, Switzerland). 2021;11(5).
70. Dai C, Sun Y. Robotic Manipulation of Reproductive Cells: Springer; 2023.
71. Prelaj A, Miskovic V, Zanitti M, Trovo F, Genova C, Viscardi G, et al. Artificial intelligence for predictive biomarker discovery in immuno-oncology: a systematic review. Annals of oncology : official journal of the European Society for Medical Oncology. 2024;35(1):29-65.
72. Nugmanova Z. Integrated Reference Single-cell RNA seq Atlas of Healthy Human Female Tissues to Expand the Computational Drug Target Discovery Approaches for Female-Directed Non-hormonal Contraceptives. 2024.
73. Chen C, Wang J, Pan D, Wang X, Xu Y, Yan J, et al. Applications of multi-omics analysis in human diseases. MedComm. 2023;4(4):e315.
74. Verma KK, Grabow KM, Koch RS, Friedmann DP, Tarbox MB. Artificial intelligence in melanoma diagnosis: ethical considerations and clinical implementation. Proceedings (Baylor University Medical Center). 2025;38(4):577-8.
75. Sümer Ö, Huber T, Duong D, Ledgister Hanchard SE, Conati C, André E, et al. Evaluation of a Deep Learning and XAI based Facial Phenotyping Tool for Genetic Syndromes: A Clinical User Study. medRxiv : the preprint server for health sciences. 2025.
76. Chavez Badiola A. Artificial Intelligence (AI) for embryo ranking and its use in human assisted reproduction: University of Kent; 2024.
77. Zaninovic N, Rosenwaks Z. Artificial intelligence in human in vitro fertilization and embryology. Fertility and sterility. 2020;114(5):914-20.
78. Rebboah E. Mapping Transcriptional Regulation of Cell Types and States Using Systems Genetics in Mouse: University of California, Irvine; 2024.
79. Shoham Z. Artificial Intelligence in Reproductive Medicine: Transforming Assisted Reproductive Technologies. Journal of IVF-Worldwide. 2025;3(2):1-8.
80. Medenica S, Zivanovic D, Batkoska L, Marinelli S, Basile G, Perino A, et al. The future is coming: artificial intelligence in the treatment of infertility could improve assisted reproduction outcomes—the value of regulatory frameworks. Diagnostics. 2022;12(12):2979.
81. Nogueira M, Aparício SL, Duarte I, Silvestre M. Artificial Intelligence's Role in Improving Adverse Pregnancy Outcomes: A Scoping Review and Consideration of Ethical Issues. Journal of Clinical Medicine. 2025;14(11):3860.
82. Wong E, Bermudez-Cañete A, Campbell MJ, Rhew DC. Bridging the digital divide: A practical roadmap for deploying medical artificial intelligence technologies in low-resource settings. Population Health Management. 2025;28(2):105-14.
83. Glatstein I, Chavez-Badiola A, Curchoe CL. New frontiers in embryo selection. Journal of assisted reproduction and genetics. 2023;40(2):223-34.
84. Akande OA. ARCHITECTING DECENTRALIZED AI FRAMEWORKS FOR MULTI-MODAL HEALTH DATA FUSION TO ADVANCE EQUITABLE AND PERSONALIZED MEDICINE.
85. Hammer HL, Thambawita V, Riegler MA. Foundation models: the next level of AI in ART. Human Reproduction. 2025;40(9):1595-604.
86. Tesarik J. Noninvasive biomarkers of human embryo developmental potential. International Journal of Molecular Sciences. 2025;26(10):4928.
87. Wu YC, Chia-Yu Su E, Hou JH, Lin CJ, Lin KB, Chen CH. Artificial intelligence and assisted reproductive technology: A comprehensive systematic

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review. Taiwanese journal of obstetrics & gynecology. 2025;64(1):11-26.
88. Sciorio R, Tramontano L, Greco PF, Greco E. Morphological assessment of oocyte quality during assisted reproductive technology cycle. JBRA assisted reproduction. 2024;28(3):511-20.
89. Wu Y-C, Su EC-Y, Hou J-H, Lin C-J, Lin KB, Chen C-H. Artificial intelligence and assisted reproductive technology: A comprehensive systematic review. Taiwanese Journal of Obstetrics and Gynecology. 2025;64(1):11-26.
90. Olawade DB, Teke J, Adeleye KK, Weerasinghe K, Maidoki M, David-Olawade AC. Artificial intelligence in in-vitro fertilization (IVF): A new era of precision and personalization in fertility treatments. Journal of gynecology obstetrics and human reproduction. 2025;54(3):102903.
91. Kawakita T, Wong MS, Gibson KS, Gupta M, Gimovsky AC, Moussa HN, et al. Application of Generative AI to Enhance Obstetrics and Gynecology Research. American journal of perinatology. 2025.
92. Upadhyay U, Gradisek A, Iqbal U, Dhar E, Li YC, Syed-Abdul S. Call for the responsible artificial intelligence in the healthcare. BMJ health & care informatics. 2023;30(1).
93. Reig A, Herlihy N, Cakiroglu Y, Whitehead C, Tiras B, Scott Jr RT, et al. Reply: Follicular activation, not ovarian rejuvenation: terminology matters, but outcomes remain unchanged after platelet-rich plasma administration. Human Reproduction. 2025;40(4):766-7.
94. Stocks BT, Oppenheimer AG, Campbell KJ, Lindsey JP, Kohn TP, Alexander JM, et al. Optimal restoration of spermatogenesis after testosterone therapy using human chorionic gonadotropin and follicle-stimulating hormone. Fertility and sterility. 2025;123(4):607-15.