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Review

Artificial intelligence in *in-vitro* fertilization (IVF): A new era of precision and personalization in fertility treatments

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ABSTRACT

In-vitro fertilization (IVF) has been a transformative advancement in assisted reproductive technology. However, success rates remain suboptimal, with only about one-third of cycles resulting in pregnancy and fewer leading to live births. This narrative review explores the potential of artificial intelligence (AI), machine learning (ML), and deep learning (DL) to enhance various stages of the IVF process. Personalization of ovarian stimulation protocols, gamete selection, and embryo annotation and selection are critical areas where AI may benefit significantly. AI-driven tools can analyze vast datasets to predict optimal stimulation protocols, potentially improving oocyte quality and fertilization rates. In sperm and oocyte quality assessment, AI can offer precise, objective analyses, reducing subjectivity and standardizing evaluations. In embryo selection, AI can analyze time-lapse imaging and morphological data to support the prediction of embryo viability, potentially aiding implantation outcomes. However, the role of AI in improving clinical outcomes remains to be confirmed by large-scale, well-designed clinical trials. Additionally, AI has the potential to enhance quality control and workflow optimization within IVF laboratories by continuously monitoring key performance indicators (KPIs) and facilitating efficient resource utilization. Ethical considerations, including data privacy, algorithmic bias, and fairness, are paramount for the responsible implementation of AI in IVF. Future research should prioritize validating AI tools in diverse clinical settings, ensuring their applicability and reliability. Collaboration among AI experts, clinicians, and embryologists is essential to drive innovation and improve outcomes in assisted reproduction. AI's integration into IVF holds promise for advancing patient care, but its clinical potential requires careful evaluation and ongoing refinement.

1. Introduction

In-vitro fertilization (IVF) has been a groundbreaking advancement in assisted reproductive technology since the birth of the first "test-tube baby" in 1978 [1]. This technique has offered hope to millions of couples struggling with infertility, providing an alternative pathway to parenthood. IVF has evolved significantly over the past four decades, incorporating various technological advancements to enhance its efficacy [2]. However, despite these innovations, the success rates of IVF remain suboptimal, with only approximately one-third of cycles resulting in pregnancy and an even smaller proportion leading to the birth of a healthy baby. It is important to note that while artificial intelligence (AI) offers the potential to optimize certain aspects of IVF, clinical validation of AI's impact on improving live birth rates remains limited.

The challenges faced in IVF involve complex biological, medical, and technical factors [3,4]. One of the primary hurdles is the variability in patient response to ovarian stimulation protocols [5,6]. Personalizing these protocols to suit individual patient profiles is crucial for optimizing the quantity and quality of oocytes retrieved [7–9]. However, AI is not capable of directly enhancing oocyte quality; instead, it can help in

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tailoring stimulation protocols by identifying predictive factors for optimal responses [10,11]. Even with personalized approaches, predicting patient response remains challenging, leading to inconsistent outcomes. Furthermore, the selection of high-quality gametes and embryos is essential for improving fertilization rates and embryo viability [12,13], yet current methods heavily rely on subjective assessments by embryologists.

To address these complexities, AI encompasses various computational techniques that enable machines to mimic human intelligence [14]. Machine learning (ML), a subset of AI, involves the development of algorithms that can learn from and make predictions based on data [15]. Deep learning (DL), a more advanced subset of ML, utilizes neural networks with multiple layers to analyze complex patterns in large datasets [16]. These technologies have already demonstrated potential in various medical fields, including radiology [17], oncology, and genomics by providing precise, data-driven insights that enhance clinical decision-making [16].However, the application of AI in IVF remains in its early stages, and while early results are promising, comprehensive clinical validation is still required before AI can be routinely integrated into IVF practices [18].

Recent studies have shown that AI, ML, and DL present opportunities to transform IVF practices [18–21]. Integrating AI into IVF can potentially address several critical areas that influence the procedure's success. For instance, AI-driven tools can analyze vast amounts of patient data to identify patterns and correlations that may not be apparent to human practitioners. This capability can enhance the personalization of ovarian stimulation protocols, ensuring that each patient receives the most suitable treatment plan [11]. Additionally, AI can improve gamete and embryo selection by providing objective assessments based on detailed morphological and genetic data [22,23], reducing the subjectivity and variability associated with manual evaluations. However, it is crucial to acknowledge that while AI can standardize and streamline certain procedures, its direct effect on improving IVF success rates requires further large-scale clinical trials [24].

Moreover, AI can play a significant role in the quality control of IVF laboratories [24,25]. By continuously monitoring key performance indicators and laboratory conditions, AI systems can ensure that the highest standards are maintained, thus increasing the consistency and reliability of IVF outcomes. The scheduling and workflow optimization capabilities of AI can also enhance the efficiency of IVF procedures, minimizing delays and ensuring the timely handling of gametes and embryos [26]. Yet, the impact of these efficiencies on clinical outcomes like pregnancy and live birth rates remains to be fully validated in a broader clinical context [25].

Despite significant advancements in assisted reproductive technology, the success rates of *in-vitro* fertilization (IVF) remain disappointingly low, with only about one-third of cycles resulting in pregnancy and even fewer leading to live births. This highlights a pressing need for more effective and reliable methods to enhance IVF outcomes. The rationale for this review is rooted in the potential of artificial intelligence (AI), machine learning (ML), and deep learning (DL) to address these challenges by providing objective, data-driven tools that can optimize various stages of the IVF process. The novelty of this review lies in its comprehensive examination of how these advanced technologies can be integrated into IVF practices to improve patient-specific stimulation protocols, gamete and embryo selection, and overall laboratory efficiency. The primary objectives of this narrative review are to explore current evidence supporting the use of AI, ML, and DL in IVF, to identify the potential benefits and limitations of these technologies, and to outline future directions for research and clinical implementation. This

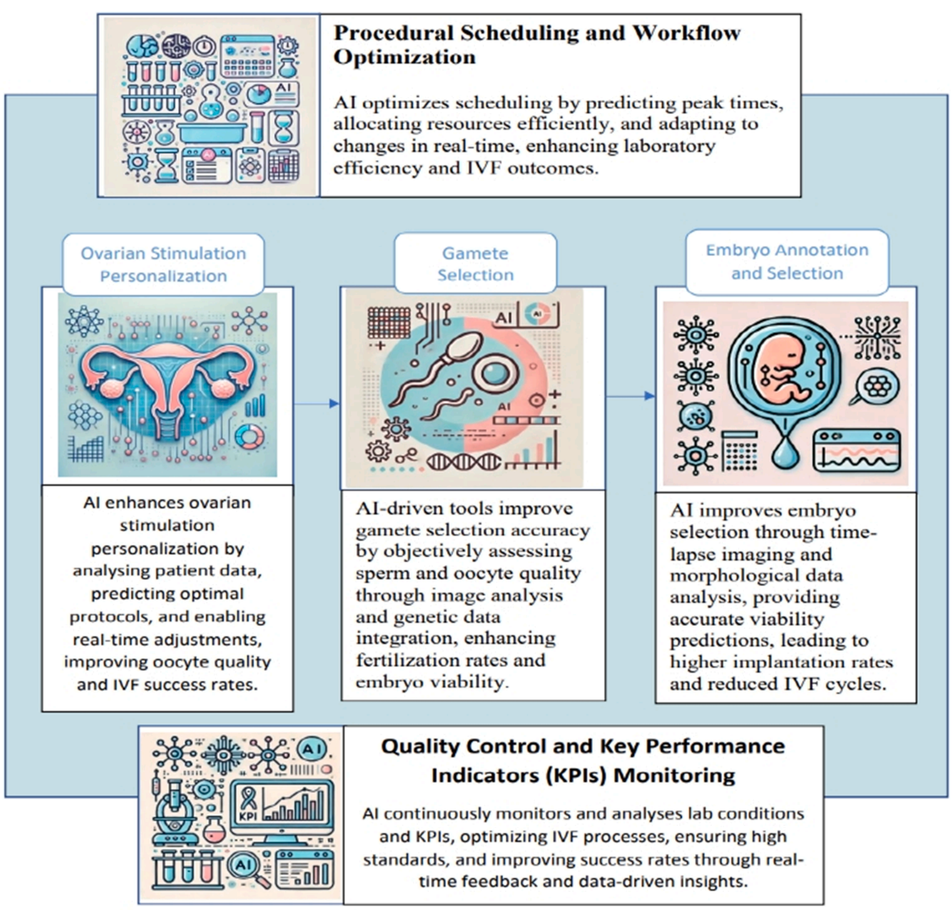

Fig. 1. Different applications of AI integrated into IVF practices.

review aims to contribute to ongoing efforts to enhance IVF success rates and reduce patient emotional and financial burdens by synthesizing the latest findings and proposing new avenues for innovation. Fig. 1 below highlights different applications of AI integrated into IVF practices.

2. Methods

2.1. Literature search

A comprehensive literature search was conducted to gather relevant studies and articles on the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in *in-vitro* fertilization (IVF). The literature databases searched included PubMed, Scopus, Web of Science, and Google Scholar. The search was performed using a combination of keywords and MeSH terms, such as "artificial intelligence," "machine learning," "deep learning," "*in-vitro* fertilization," "IVF," "ovarian stimulation," "oocyte quality," "embryo selection," "sperm selection," and "IVF outcomes." The search was limited to articles published in English from January 2000 to July 2024 to capture the most recent and relevant advancements in the field.

While this review adhered to a structured methodology, it is important to clarify that it is a narrative review, not a systematic one. The goal was to explore and synthesize emerging themes and advancements in the application of AI in IVF, rather than to evaluate the efficacy of interventions systematically. Thus, the approach prioritized conceptual synthesis and thematic organization over strict quantitative analysis.

2.2. Inclusion and exclusion criteria

The review included peer-reviewed articles and reviews that addressed the use of AI, ML, and DL in various aspects of IVF. Relevant studies discussed AI's impact on ovarian stimulation protocols, gamete selection, embryo assessment, and IVF laboratory quality control. Articles providing data on AI-driven IVF outcomes, such as pregnancy rates, live birth rates, and embryo viability, were considered. The search initially yielded 315 articles. After reviewing titles and abstracts, 118 articles were deemed potentially relevant. Following a detailed full-text review, 53 studies were included based on inclusion criteria, as summarized in Fig. 2. Articles not directly related to IVF, those focusing on other reproductive technologies, non-English publications, and studies without a clear focus on applying AI, ML, or DL in IVF were excluded.

2.3. Risk of bias evaluation

As this review is a narrative synthesis, it does not systematically evaluate the risk of bias for included studies. However, efforts were made to ensure reliability by selecting studies published in peer-reviewed journals and critically appraising their methodological rigor during data extraction.

2.4. Synthesis of results

Findings from the selected studies were synthesized narratively, focusing on conceptual and thematic insights into AI applications across the IVF process. The studies were grouped based on key aspects of IVF, including ovarian stimulation, gamete selection, embryo selection, and laboratory management. The themes identified during data extraction were structured to reflect critical areas of AI integration in IVF including personalization of ovarian stimulation protocols, gamete and embryo selection, quality control in IVF laboratories, and workflow optimization. The narrative synthesis critically analyzed AI applications'

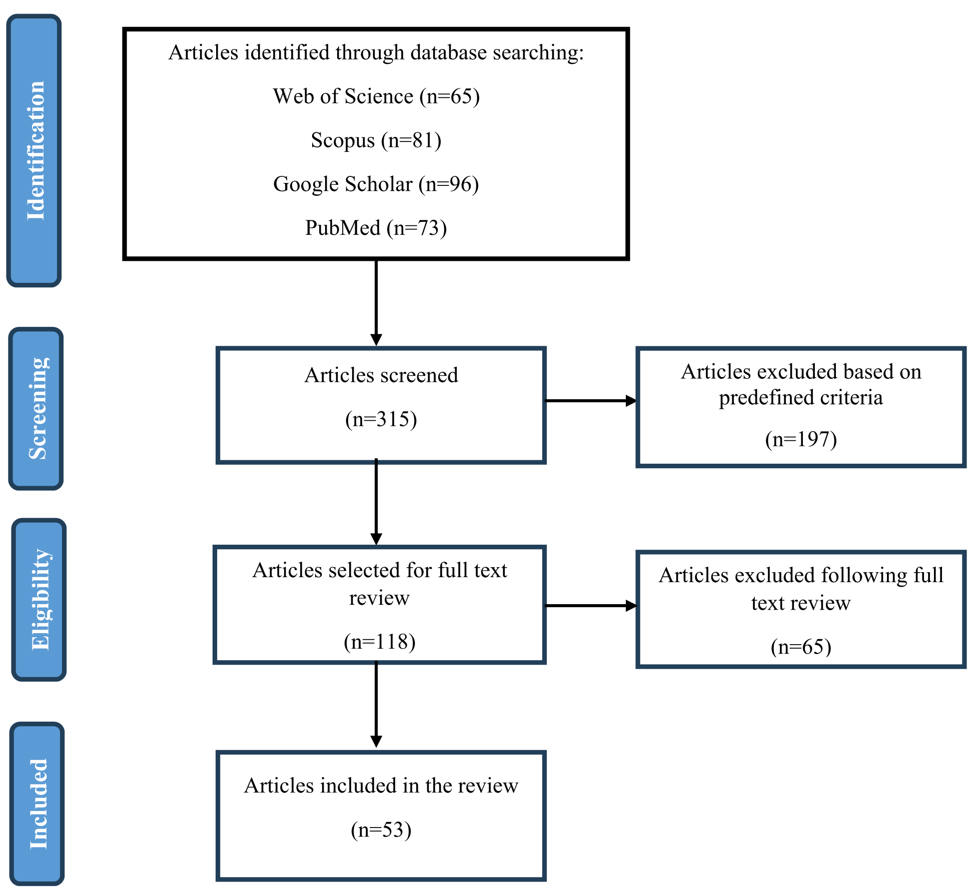

Fig. 2. PRISMA flow diagram of the article selection process.

potential benefits and limitations, aiming to provide a comprehensive overview of current evidence and highlight areas for future research.

3. Personalization of ovarian stimulation protocols

Ovarian stimulation protocols are critical to *in-vitro* fertilization (IVF) success as they optimize the number and quality of oocytes retrieved [5,27]. These protocols typically involve the administration of gonadotrophins to stimulate the ovaries to produce multiple follicles and to retrieve a sufficient number of mature oocytes that can be fertilized to create viable embryos [28]. Personalization of ovarian stimulation has become increasingly important due to the variability in patient characteristics such as age, ovarian reserve, and hormonal profile [29,30]. For instance, younger patients with a higher ovarian reserve may require different stimulation protocols compared to older patients or those with diminished ovarian reserve. Despite personalized approaches, predicting individual patient responses to stimulation remains challenging. Suboptimal stimulation can lead to various issues, including ovarian hyperstimulation syndrome (OHSS), poor oocyte quality, and, ultimately, lower IVF success rates [31].

Artificial intelligence (AI) can potentially revolutionize the personalization of ovarian stimulation protocols by leveraging vast datasets and advanced analytical techniques [21,32]. Recent advances in AI, particularly in machine learning (ML) and deep learning (DL), have shown promise in improving the accuracy and efficacy of these protocols. AI can analyze extensive datasets comprising patient characteristics, historical responses to stimulation protocols, and IVF outcomes [33,34]. AI can provide insights that may elude traditional analysis by identifying patterns and correlations within these datasets [35]. For instance, AI can identify subtle correlations between specific patient profiles and their responses to different stimulation protocols, enabling more precise treatment tailoring.

Machine learning algorithms can develop predictive models to estimate each patient's optimal type and dose of gonadotropins [36]. These models consider various factors, including age, body mass index (BMI), antral follicle count (AFC), and anti-Müllerian hormone (AMH) levels. AI models can predict the best day for monitoring a patient, trigger day options, and the number of oocytes [11]. AI systems can integrate data from previous IVF cycles to refine predictions for future treatments. This iterative learning process allows the AI to improve its recommendations continuously. By incorporating historical patient data, AI can enhance the personalization of stimulation protocols, resulting in improved clinical outcomes. Moreover, AI can also facilitate real-time adjustments to stimulation protocols [37]. By monitoring patients' responses during the stimulation phase, AI algorithms can recommend modifications to the dosage or type of gonadotropins. This dynamic approach ensures that the protocols are constantly optimized to achieve the best possible outcomes, reducing the incidence of complications like OHSS and enhancing overall treatment efficacy [21].

4. Gamete selection

Gamete selection is a pivotal step in the *in-vitro* fertilization (IVF) process, significantly impacting fertilization success rates and subsequent embryo development [38]. Accurately selecting high-quality sperm and oocytes can enhance the likelihood of successful fertilization, implantation, and a successful pregnancy [39]. While effective to some extent, traditional methods of gamete selection are often subjective and reliant on embryologists' expertise [40]. Advances in artificial intelligence (AI) and deep learning (DL) offer the potential to revolutionize gamete selection by providing objective, data-driven tools that can improve the accuracy and consistency of these assessments [41].

4.1. Sperm classification and selection

Traditional sperm selection methods rely heavily on manual assessment and basic laboratory techniques such as visual evaluation of motility and morphology using microscopy [42,43]. These methods are inherently subjective and can vary significantly between practitioners. Manual assessment is also time-consuming and may not always accurately predict the fertilization potential of sperm [42]. AI and DL technologies can significantly enhance sperm selection by analyzing motility, morphology, and other relevant parameters with high precision [24,44]. While some studies indicate comparable outcomes between AI-based and traditional methods, DL models, trained on large datasets of sperm images and associated outcomes, can classify sperm quality more accurately than traditional methods [45,46]. These models can identify subtle morphological features and motility patterns that correlate with successful fertilization. For instance, DL algorithms can analyze high-resolution video footage of sperm movement to assess motility parameters such as velocity, linearity, and amplitude of lateral head displacement [47]. By providing a more objective and precise assessment of sperm quality, AI and DL can improve the chances of selecting the best sperm for fertilization. This not only increases the likelihood of successful fertilization but also enhances the overall quality of the resulting embryos. AI-driven sperm selection can be particularly beneficial in cases of male factor infertility, where the selection of the highest-quality sperm is critical for achieving positive outcomes.

4.2. Oocyte quality assessment

Oocyte quality is a crucial determinant of successful fertilization and subsequent embryo development [48,49]. Traditional assessment methods for oocyte quality primarily rely on morphological criteria observed under a microscope, such as the appearance of the zona pellucida, cytoplasm, and polar body [50]. However, these assessments are subjective and can vary between embryologists, leading to inconsistencies in oocyte quality assessment. AI offers a transformative approach to oocyte quality assessment by providing objective analyses based on high-resolution images of oocytes [11,51]. Advanced image analysis techniques powered by AI can identify subtle features that correlate with oocyte quality, which may not be discernible through manual evaluation. For example, AI algorithms can assess the ooplasm's homogeneity, the zona pellucida's integrity, and the presence of cytoplasmic inclusions or vacuoles, all of which are important indicators of oocyte health.

Furthermore, AI can integrate data from multiple imaging modalities, such as time-lapse microscopy and confocal imaging, to comprehensively assess oocyte quality. Time-lapse imaging allows continuous monitoring of oocyte development, providing dynamic information that AI can analyze to predict developmental potential [52]. By combining morphological data with dynamic developmental patterns, AI can enhance the accuracy of oocyte quality assessment, leading to better fertilization rates and higher-quality embryos.

4.3. Integration of genetic data

In addition to morphological assessments, the integration of genetic data into AI-driven gamete selection processes holds significant promise. Preimplantation genetic testing (PGT) can identify chromosomal abnormalities and genetic disorders in oocytes and embryos [53]. AI algorithms can analyze genetic data alongside morphological and developmental information to provide a more holistic assessment of gamete quality [54]. This integrated approach can improve the selection of genetically normal gametes, thereby increasing the chances of a successful pregnancy and reducing the risk of genetic disorders.

Table 1 provides an overview of how AI applications and models can enhance the various aspects of gamete selection in IVF, improving precision, objectivity, and overall outcomes.

Table 1
AI applications in gamete selection.

Aspect of Gamete Selection	Traditional Methods	AI Applications/Models Used	Benefits of AI Applications
Sperm Classification and Selection [44]	Manual assessment using microscopy for motility and morphology	DL models (e.g., Convolutional Neural Networks) analyzing high-resolution images and video footage	- Increased precision and objectivity in motility and morphology assessment - Identification of subtle features correlating with fertilization potential - Improved consistency and reliability in sperm selection
Motility Analysis [55]	Visual inspection of sperm movement under a microscope	Computer Vision and DL models analyzing motility patterns	- Detailed quantification of motility parameters - Enhanced detection of optimal motile sperm - Reduced subjectivity in motility assessment
Morphology Assessment [56]	Kruger's strict criteria assessed visually by embryologists	Machine Learning models (e.g., Support Vector Machines) trained on large datasets of sperm images	- Objective classification of sperm morphology - Higher accuracy in identifying sperm with optimal morphology - Consistency across different observers and laboratories
Oocyte Quality Assessment [51,57]	Morphological evaluation of zona pellucida, cytoplasm, and polar body	AI-based image analysis (e.g., Convolutional Neural Networks) on high-resolution oocyte images	- Objective analysis of subtle morphological features - Integration of multiple imaging modalities - Improved selection of high-quality oocytes
Real-time Adjustments [58,59]	Adjustments based on manual observation and clinical judgment	AI-driven real-time recommendations for sperm and oocyte quality assessment	- Dynamic optimization of selection criteria - Immediate feedback for embryologists - Enhanced decision-making during the selection process
Data Integration from Previous Cycles [51]	Manual review of patient history and past IVF outcomes	AI models integrating historical patient data for personalized predictions	- Improved personalization of gamete selection - Continuous refinement of selection criteria based on past outcomes - Enhanced IVF success rates through tailored approaches

5. Embryo annotation and selection

Embryo annotation and selection are critical steps in the *in-vitro* fertilization (IVF) process, significantly influencing the likelihood of successful implantation and pregnancy [60,61]. Traditional methods for selecting embryos primarily rely on morphological assessment, where embryologists visually evaluate the embryos under a microscope. This assessment typically considers cell number, symmetry, and fragmentation factors. Some clinics also incorporate genetic testing, such as preimplantation genetic testing (PGT), to identify chromosomal abnormalities [62,63]. However, these methods are inherently subjective and can vary between embryologists, leading to inconsistent and sometimes inaccurate predictions of embryo viability [64].

5.1. Traditional methods

Morphological assessment of embryos involves examining their appearance at various stages of development [64]. On Day 3, embryos are usually evaluated based on the number and regularity of blastomeres and the degree of fragmentation. On Day 5, the focus shifts to the formation and quality of the blastocyst, including the appearance of the inner cell mass and the trophectoderm [65]. While these assessments provide valuable information, they do not always correlate with the embryo's ability to implant and develop into a healthy pregnancy. These evaluations are subjective, with significant variability between embryologists' assessments. Genetic testing, such as PGT, can provide additional insights into the chromosomal status of embryos [53]. By identifying aneuploidies, genetic testing can help select embryos with the highest potential for successful implantation [66]. However, PGT is invasive, expensive, and not universally available. Moreover, it cannot assess an embryo's functional potential beyond its chromosomal makeup, leaving gaps in predicting overall viability.

5.2. AI in embryo selection

Artificial intelligence (AI) and deep learning (DL) technologies have the potential to revolutionize embryo selection by providing more objective, accurate, and comprehensive assessments [14,15]. AI can analyze large datasets of time-lapse imaging and morphological data to predict embryo viability more precisely than traditional methods. Time-lapse imaging systems capture continuous images of embryos as they develop, providing a detailed record of their morphological changes. AI algorithms can analyze these time-lapse videos to identify patterns and developmental milestones associated with successful implantation and development [67]. AI can provide a more dynamic and nuanced assessment of embryo quality by examining parameters such as cleavage patterns, blastocyst formation, and the timing of key developmental events. Recent studies have demonstrated that AI models analyzing time-lapse imaging can significantly improve the accuracy of embryo viability predictions [23]. For instance, AI can detect subtle morphological changes and dynamic behaviors difficult for human observers to discern. These models can predict implantation potential with higher accuracy, leading to better embryo selection for transfer and increased implantation rates.

In addition to time-lapse imaging, AI can enhance the traditional morphological assessment of embryos. Deep learning models, particularly convolutional neural networks (CNNs), can be trained on large datasets of embryo images to recognize features that correlate with high viability [68]. These models can analyze static images of embryos at various stages of development, providing an objective assessment that reduces inter-embryologist variability. AI-driven morphological assessments can identify features such as blastomere symmetry, cell junction quality, and the degree of fragmentation with greater precision than manual evaluations. By combining these assessments with time-lapse imaging data, AI provides a comprehensive analysis encompassing static and dynamic aspects of embryo development.

Table 2
AI applications in embryo annotation and selection.

Aspect of Embryo Selection	Traditional Methods	AI Models/Tools Used	Benefits of AI Applications
Morphological Assessment [68]	Visual assessment of cell number, symmetry, and fragmentation	Convolutional Neural Networks (CNNs) analyzing static images of embryos	- Objective and consistent assessment - Reduced inter-embryologist variability - Enhanced identification of viable embryos
Time-Lapse Imaging Analysis [61]	Manual observation of developmental stages	Time-lapse imaging systems with AI (e.g., EmbryoScope, Eeva)	- Continuous monitoring of embryo development - Detection of subtle morphological changes and dynamic behaviors - Improved prediction of implantation potential
Dynamic Monitoring [23]	Periodic manual checks of embryo development	AI algorithms analyzing time-lapse videos	- Identification of key developmental milestones - More accurate assessment of embryo quality - Better selection of embryos for transfer
Genetic Data Integration [53].	Preimplantation Genetic Testing (PGT) for aneuploidies	AI models integrating genetic, morphological, and developmental data	- Comprehensive assessment of embryo quality - Increased selection accuracy for genetically normal embryos - Reduced risk of genetic disorders
Predictive Modeling [69]	Predictions based on clinical judgment and experience	Machine Learning models (e.g., Random Forest, Support Vector Machines)	- Data-driven predictions of embryo viability - Integration of diverse data sources (e.g., patient history, stimulation protocols) - Improved decision-making for embryo transfer
Real-time Adjustments [70, 71]	Adjustments based on manual observation and clinical judgment	AI-driven real-time recommendations	- Dynamic optimization of selection criteria - Immediate feedback for embryologists - Enhanced decision-making during the selection process
Scoring Systems [72,73]	Embryo grading based on visual criteria	AI-generated scoring systems (e.g., Life Whisperer, iDAScore)	- Objective and reproducible scoring - Better prediction of implantation and pregnancy outcomes - Streamlined workflow in the embryology lab
Outcome Prediction [74]	Predictions based on historical success rates	AI models analyzing historical IVF data (e.g., IVF outcome prediction models)	- Personalized predictions of success rates - Tailored treatment recommendations - Higher chances of successful pregnancy with fewer cycles
Dynamic Monitoring (Time-lapse Imaging) [52]	Periodic manual observation of oocyte development stages	AI models analyzing time-lapse video to assess developmental potential	- Continuous monitoring of oocyte development - Identification of optimal developmental patterns - Prediction of fertilization and embryo development potential
Genetic Assessment Integration [53]	Preimplantation Genetic Testing (PGT) based on chromosomal analysis	AI models combining genetic data with morphological and developmental information	- Comprehensive assessment of genetic and morphological quality - Increased selection accuracy for genetically normal gametes - Reduced risk of genetic disorders in resulting embryos

AI's ability to integrate and analyze diverse datasets allows for the development of predictive models that can forecast embryo viability [69]. These models can incorporate morphological data, time-lapse imaging, and genetic information to provide a holistic assessment. By identifying embryos with the highest potential for successful implantation and development, AI can increase implantation rates and reduce the number of cycles required to achieve a successful pregnancy [22]. For example, machine learning algorithms can be trained on historical IVF data, including patient demographics, stimulation protocols, and outcomes. These models can then predict the likelihood of success for new patients, helping clinicians make more informed decisions about embryo selection and transfer.

Table 2 provides a comprehensive overview of how AI models and tools are being used to enhance various aspects of embryo annotation and selection, improving precision, objectivity, and overall IVF outcomes.

6. Quality control and key performance indicators monitoring

Consistent quality control in IVF laboratories is crucial for maintaining high standards and ensuring the success of assisted reproductive technologies [75]. Quality control encompasses a range of practices to monitor and optimize laboratory conditions and procedures to achieve the best possible patient outcomes. Key performance indicators (KPIs) such as fertilization rates, blastocyst formation rates, and clinical pregnancy rates are essential metrics that reflect the laboratory's performance and overall effectiveness [76]. Monitoring these KPIs allows laboratories to identify improvement areas, ensuring that all IVF processes function optimally. High standards in quality control are not only critical for achieving successful pregnancies but also for maintaining patient trust and adhering to regulatory requirements [75.

Artificial intelligence (AI) offers significant advancements in the realm of quality control by enabling continuous monitoring and analysis of laboratory conditions and procedural outcomes [77]. Machine learning (ML) algorithms can process vast amounts of data from various sources within the laboratory, including environmental sensors, procedural logs, and patient records [78]. By analyzing this data, AI systems can identify patterns and deviations from established KPIs that may indicate potential issues or areas for improvement. For instance, AI can monitor environmental conditions such as temperature, humidity, and air quality within the laboratory to ensure they remain within optimal ranges for gamete and embryo culture. Any deviations from these parameters can be immediately flagged, allowing laboratory staff to take corrective actions before these conditions negatively impact the IVF outcomes. Additionally, AI can track procedural adherence, ensuring that protocols are followed consistently, which is crucial for maintaining the quality and viability of gametes and embryos.

AI-driven quality control systems can also provide real-time feedback and recommendations based on the analysis of KPI data [79]. For example, if fertilization rates are observed to be below expected levels, AI algorithms can analyze procedural data to identify potential causes, such as variations in sperm or oocyte handling techniques, and suggest modifications to improve outcomes [32]. Similarly, if blastocyst formation rates are suboptimal, AI can recommend adjustments in culture conditions or protocols based on historical data and current trends [20]. By continuously monitoring and optimizing laboratory conditions and procedures, AI helps ensure that each IVF process is performed to the highest standards [9,80]. This enhances the likelihood of successful pregnancies and reduces errors and variability, ultimately contributing to better patient outcomes and increased confidence in IVF treatments. Furthermore, AI's ability to analyze complex datasets and provide actionable insights can support ongoing improvements in laboratory practices. Continuous learning and adaptation of AI algorithms based on new data can drive innovations and refine IVF protocols, ensuring that laboratories remain at the forefront of assisted reproductive technologies [81]. This dynamic approach to quality control, underpinned by AI, represents a significant advancement in pursuing excellence in IVF outcomes as highlighted in Table 3.

7. Procedural scheduling and workflow optimization

Efficient scheduling and workflow management are critical in busy IVF laboratories, where timely execution of procedures is paramount for maintaining the quality of gametes and embryos [89]. Delays or inefficiencies in the workflow can lead to suboptimal conditions, which may negatively impact fertilization rates, embryo development, and overall IVF success rates. Common challenges include coordinating multiple procedures that need to occur within specific time windows, managing the availability of laboratory staff and equipment, and responding to unexpected changes, such as equipment failures or variations in patient needs. Inefficient scheduling can result in extended waiting times, increased stress for patients and staff, and potentially lower clinical outcomes [90].

Artificial intelligence (AI) offers transformative potential for optimizing scheduling and workflow management in IVF laboratories [11]. By analyzing historical data and real-time workflow patterns, AI can predict the optimal timing for various procedures, ensuring that each step is carried out at the most appropriate moment. This optimization can significantly reduce waiting times and enhance the timely handling of gametes and embryos, ultimately improving laboratory efficiency and success rates. AI can analyze extensive datasets from past cycles to identify patterns and bottlenecks in the workflow. By understanding these patterns, AI algorithms can forecast busy periods and allocate resources accordingly [91]. This ensures that critical procedures, such as oocyte retrieval, fertilization, and embryo transfer, are performed without unnecessary delays [92]. For example, AI can predict peak times for laboratory activities and suggest optimal staff scheduling to meet these demands.

Machine learning (ML) algorithms can predict the best timing for each procedure based on various factors, including patient-specific data, laboratory conditions, and historical outcomes. This predictive capability ensures that procedures are scheduled when conditions are most favorable, enhancing the quality of gametes and embryos [41]. For instance, AI can determine the optimal time for oocyte retrieval based on the maturation status of the follicles, ensuring that oocytes are collected at their peak quality [21]. AI-driven scheduling tools can adapt to unexpected changes, such as equipment malfunctions or sudden shifts in patient conditions. By continuously monitoring the workflow and available resources, AI can make real-time adjustments to the schedule, ensuring that disruptions are minimized. This adaptability is crucial in maintaining smooth operations and avoiding delays that could compromise the quality of the IVF process [57].

AI can also optimize allocating laboratory resources, including staff, equipment, and lab space. By predicting the needs for each procedure and ensuring that resources are available when needed, AI helps avoid overbooking and underutilization. This efficient allocation not only improves workflow but also enhances the working environment for laboratory staff, reducing stress and potential errors. Several AI-driven scheduling tools are being developed and implemented in IVF laboratories [93]. These tools utilize advanced algorithms to create dynamic schedules that can be adjusted in real-time based on changing conditions. For example, AI platforms can integrate data from patient management systems, laboratory information systems, and real-time monitoring devices to provide comprehensive scheduling solutions. These platforms offer features such as automatic rescheduling in response to delays, predictive analytics for resource planning, and real-time alerts for staff and patients.

AI-driven scheduling reduces waiting times by optimizing the schedule and ensuring the timely execution of procedures. This improves the overall patient experience and reduces the stress associated with the IVF process [94]. Timely handling of gametes and embryos ensures they are maintained optimally, enhancing their quality and viability. This can lead to higher fertilization rates, better embryo development, and increased success rates for IVF cycles [25]. Enhanced laboratory efficiency is another significant benefit of AI-driven scheduling. By streamlining the workflow, reducing bottlenecks, and improving overall efficiency, laboratories can handle a higher volume of cycles without compromising quality. AI's ability to adapt to unexpected changes ensures that the laboratory can respond quickly to disruptions, maintaining smooth operations and minimizing delays. Additionally, AI optimizes the allocation of resources, ensuring that staff, equipment, and lab space are used efficiently, reducing waste, and enhancing productivity.

8. Challenges of AI application in IVF

The application of artificial intelligence (AI) in *in-vitro* fertilization (IVF) presents significant challenges that must be addressed before widespread clinical adoption [93]. One major issue is the lack of large-scale clinical validation. Many AI models in IVF are developed and tested on small, single-center datasets, which limits their generalizability. These studies are often conducted in highly controlled environments with relatively homogeneous patient populations, lacking diversity in real-world clinical settings. Without robust, multi-center, randomized controlled trials that validate these models across various patient demographics and clinical contexts, the efficacy and safety of AI-driven tools remain uncertain. For instance, while some studies suggest AI improves embryo selection accuracy, few provide long-term outcome data, such as live birth rates or the health of children born through AI-guided IVF.

One reason for inconsistent findings across different centers is the lack of standardized recording and reporting practices. Variations in how data is collected, interpreted and reported can lead to discrepancies in AI performance and make it difficult to compare results across studies. For example, centers may use different criteria for evaluating embryo quality or success rates, which can influence AI model training and results. Establishing a consensus on standardized data collection, detailed recording of IVF outcomes, and uniform reporting protocols for AI applications in IVF would help ensure consistency and allow for more reliable cross-center comparisons. Such standardization would enable a more precise evaluation of AI's effectiveness across different clinical environments.

Another significant challenge is bias in the datasets used to train AI models. AI relies heavily on historical data to identify patterns and make predictions [95]. If the data used to train these algorithms does not represent the broader population, it can introduce significant bias, resulting in inequitable treatment outcomes. For example, most AI models in IVF have been developed using data from predominantly

Table 3
Quality control and key performance indicators monitoring in IVF.

Component	Traditional Methods	AI Models/Tools Used	Key Performance Indicators (KPIs)	Advantages of AI
Environmental Monitoring [76]	Manual recording and periodic checks of temperature, humidity, air quality	AI-driven environmental sensors and IoT devices	Temperature stability, humidity levels, air quality	Continuous real-time monitoring, immediate deviation alerts, consistent optimal conditions
Fertilization Rates [82]	Manual calculation and periodic analysis based on fertilization success	Machine Learning algorithms analyzing fertilization data	Number of fertilized oocytes, fertilization rate per cycle	Real-time analysis, early identification of issues, data-driven recommendations for improvement
Blastocyst Formation [83]	Visual assessment and manual recording of blastocyst development stages	Time-lapse imaging systems with AI analysis (e.g., EmbryoScope)	Blastocyst formation rate, time to blastocyst stage	Continuous monitoring, precise tracking of developmental stages, better prediction of blastocyst viability
Clinical Pregnancy Rates [76]	Retrospective analysis of clinical pregnancy outcomes	Predictive analytics models integrating multiple data sources	Clinical pregnancy rate, implantation rate	Real-time tracking, predictive insights for improving protocols, enhanced understanding of success factors
Procedural Adherence [84]	Manual checks and audits of adherence to protocols	Workflow management systems with AI (e.g., electronic lab notebooks with AI analytics)	Adherence to protocols, the incidence of deviations	Automated adherence tracking, immediate feedback on deviations, improved protocol consistency
Embryo Culture Conditions [79,85]	Manual observation and recording of cultural conditions	AI-driven monitoring systems analyzing cultural conditions	Culture media pH levels, oxygen concentration	Continuous monitoring, optimal condition maintenance, reduced variability in embryo development
Gamete and Embryo Handling [76]	Manual assessment and periodic reviews	AI algorithms analyzing handling data and procedural videos	Handling error rate, gamete/embryo viability post-handling	Identification of best practices, reduction of handling errors, consistent high-quality gamete and embryo handling
KPI Tracking and Reporting [86]	Manual compilation and analysis of KPI data	AI-based dashboards and reporting tools (e.g., Tableau with integrated AI)	Fertilization rates, blastocyst formation rates, clinical pregnancy rates	Real-time KPI tracking, automated reporting, easy identification of trends and issues
Root Cause Analysis of Failures [87]	Retrospective manual analysis of procedural failures	AI-driven root cause analysis tools (e.g., anomaly detection algorithms)	Failure rates, time to identify and correct issues	Faster identification of failure causes, data-driven insights, preventive measures implementation
Continuous Improvement [82,88]	Periodic reviews and manual updates of protocols	Continuous learning AI systems updating protocols based on new data	Improvement rate, protocol update frequency	Dynamic protocol optimization, incorporation of the latest evidence, ongoing performance enhancement

Western populations, which may not accurately reflect the diversity of reproductive health issues across different ethnicities, age groups, or socio-economic backgrounds. This bias could lead to unequal success rates, where certain patient groups benefit more from AI-guided treatment than others. Addressing this requires the development of more diverse and representative datasets encompassing a more comprehensive range of patient demographics and regular auditing of AI systems to identify and correct bias. The failure to mitigate these biases risks perpetuating health disparities in reproductive medicine.

Data privacy and security are also critical concerns in the application of AI in IVF. Given that AI systems require access to large datasets, including sensitive personal and genetic information, the potential for data breaches or misuse is a significant ethical concern [96]. Patients undergoing IVF are already in a vulnerable position, and the improper handling of their data could lead to privacy violations, discrimination, or other harm. Current regulatory frameworks such as the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States offer guidance on protecting patient information, but the use of AI necessitates even stricter protocols [97–99]. The integration of AI into clinical practice demands robust encryption methods, secure storage solutions, and strict access controls to safeguard patient data at every stage of the process.

In addition to privacy concerns, ethical transparency remains a crucial challenge in AI-driven IVF. Many AI algorithms function as "black boxes," meaning that their decision-making processes are not easily interpretable by clinicians or patients [100,101]. This lack of transparency can lead to challenges in clinical practice, where healthcare providers may struggle to explain or justify AI-driven recommendations to patients. For example, suppose an AI model suggests the selection of one embryo over another without a clear rationale. In that case, it may be difficult for clinicians to gain patient trust or confidence. Moreover, AI algorithms typically base their recommendations on statistical patterns rather than considering individual patient preferences, lifestyle factors, or other clinical nuances that human judgment might factor into decision-making. This can result in over-reliance on AI systems, where clinicians follow AI recommendations without thoroughly evaluating their relevance or applicability to the patient's case [96,102]. Developing more interpretable AI models and ensuring clinicians are trained to critically assess AI-generated outputs in the context of their professional expertise are essential.

9. Conclusion

Artificial intelligence (AI), machine learning (ML), and deep learning (DL) have the potential to significantly transform *in-vitro* fertilization (IVF) practices by providing objective, data-driven tools that enhance various stages of the IVF process. These technologies can personalize ovarian stimulation protocols, ensuring that each patient receives the most effective treatment based on their unique characteristics. By optimizing gamete selection through precise assessments of sperm and oocyte quality, AI can improve fertilization rates and embryo viability. Additionally, AI-driven embryo selection can lead to higher implantation success rates, reducing the number of cycles required to achieve pregnancy and thus lowering the emotional and financial burdens on patients [39]. Integrating AI into quality control and workflow optimization further enhances the efficiency and effectiveness of IVF laboratories. AI's ability to continuously monitor and analyze key performance indicators (KPIs) helps maintain high standards and consistent outcomes. Moreover, AI-driven scheduling and resource management can streamline laboratory operations, minimizing delays and ensuring the timely handling of gametes and embryos.

Despite the promising benefits, the application of AI in IVF must be approached with careful consideration of ethical implications. Ensuring data privacy and security is paramount to protect sensitive patient information. AI algorithms must be trained on diverse datasets to avoid biases and ensure fairness and inclusivity in care. Regular audits and updates of AI models are necessary to maintain their accuracy and mitigate any emerging biases. Continued research and development are crucial to refine AI technologies further and validate their efficacy in clinical settings. Collaborative efforts between AI experts, reproductive endocrinologists, embryologists, and ethicists will be essential to address the challenges and maximize the potential of AI in IVF. By adhering to ethical standards and continuously improving AI applications, the IVF field can offer more effective, equitable, and efficient treatments, ultimately enhancing the overall success rates and patient experiences in assisted reproductive technology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Fishel S. First *in vitro* fertilization baby—This is how it happened. Fertil Steril 2018;110(1):5–11.
[2] Graham ME, Jelin A, Hoon Jr AH, Wilms Floet AM, Levey E, Graham EM. Assisted reproductive technology: short-and long-term outcomes. Dev Med Child Neurol 2023;65(1):38–49.
[3] Klitzman R. Unconventional combinations of prospective parents: ethical challenges faced by IVF providers. BMC Med Ethics 2017;18:1–13.
[4] Ferber S, Marks NJ, Mackie V. IVF and assisted reproduction. Springer; 2020.
[5] Alper MM, Fauser BC. Ovarian stimulation protocols for IVF: is more better than less? Reprod Biomed Online 2017;34(4):345–53.
[6] Razafintsalama-Bourdet M, Bah M, Amand G, Vienet-Lègue L, Pietin-Vialle C, Bry-Gauillard H, et al. Random antral follicle count performed on any day of the menstrual cycle has the same predictive value as AMH for good ovarian response in IVF cycles. J Gynecol Obstet Hum Reprod 2022;51(1):102233.
[7] Jirge PR, Patil MM, Gutgutia R, Shah J, Govindarajan M, Roy VS, et al. Ovarian stimulation in assisted reproductive technology cycles for varied patient profiles: an Indian perspective. J Hum Reprod Sci 2022;15(2):112–25.
[8] Palinska-Rudzka K, Mathur R. Principles of controlled ovarian stimulation for assisted reproduction. Obstet Gynaecol Reprod Med 2023;33(4):91–6.
[9] Canon C, Leibner L, Fanton M, Chang Z, Suraj V, Lee JA, et al. Optimizing oocyte yield utilizing a machine learning model for dose and trigger decisions, a multi-center, prospective study. Sci Rep 2024 20;14(1):18721 [Internet]2024 [cited] Available from, https://www.nature.com/articles/s41598-024-69165-1.
[10] Fanton M, Nutting V, Solano F, Maeder-York P, Hariton E, Barash O, et al. An interpretable machine learning model for predicting the optimal day of trigger during ovarian stimulation. Fertil Steril 2024;118(1):101–8 [Internet]. 2022 [citedOct 20]Available from, https://www.sciencedirect.com/science/article/pii/S0015028222002448.
[11] Letterie G, MacDonald A, Shi Z. An artificial intelligence platform to optimize workflow during ovarian stimulation and IVF: process improvement and outcome-based predictions. Reprod Biomed Online 2022;44(2):254–60.
[12] Oseguera-López I, Ruiz-Díaz S, Ramos-Ibeas P, Pérez-Cerezales S. Novel techniques of sperm selection for improving IVF and ICSI outcomes. Front Cell Dev Biol 2019;7:298.
[13] Chorya JB, Sutaria TV, Chaudhari RK, Chaudhari CF. Impact of gamete health on fertilization and embryo development: an overview. Asian Pac J Reprod 2022;11(5):201–7.
[14] Konar A. Artificial intelligence and soft computing: behavioral and cognitive modeling of the human brain. CRC press; 2018.
[15] Alzubi J, Nayyar A, Kumar A. Machine learning from theory to algorithms: an overview. J Phys Conf Ser 2018:012012.
[16] Sarker IH. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. SN Comput Sci 2021;2(6):420.
[17] Najjar R. Redefining radiology: a review of artificial intelligence integration in medical imaging. Diagnostics 2023;13(17):2760.
[18] Raimundo JM, Cabrita P. Artificial intelligence at assisted reproductive technology. Procedia Comput Sci 2021;181:442–7.
[19] Goyal A, Kuchana M, Ayyagari KPR. Machine learning predicts live-birth occurrence before *in-vitro* fertilization treatment. Sci Rep 2020;10(1):20925.
[20] Cimadomo D, Chiappetta V, Innocenti F, Saturno G, Taggi M, Marconetto A, et al. Towards automation in IVF: pre-clinical validation of a deep learning-based embryo grading system during PGT-A cycles. J Clin Med 2023;12(5):1806.
[21] Hariton E, Pavlovic Z, Fanton M, Jiang VS. Applications of artificial intelligence in ovarian stimulation: a tool for improving efficiency and outcomes. Fertil Steril 2023;120(1):8–16.
[22] Fitz VW, Kanakasabapathy MK, Thirumalaraju P, Kandula H, Ramirez LB, Boehnlein L, et al. Should there be an "AI" in TEAM? Embryologists selection of high implantation potential embryos improves with the aid of an artificial intelligence algorithm. J Assist Reprod Genet 2021;38:2663–70.
[23] Kragh MF, Karstoft H. Embryo selection with artificial intelligence: how to evaluate and compare methods? J Assist Reprod Genet 2021;38(7):1675–89.
[24] Cherouveim P, Velmahos C, Bormann CL. Artificial intelligence for sperm selection—A systematic review. Fertil Steril 2023;120(1):24–31.
[25] Khan HL, Khan S, Bhatti S, Abbas S. Role of artificial intelligence in quality assurance in ART: a review. Fertil Reprod 2023;5(01):1–7.
[26] Gardner DK. The way to improve ART outcomes is to introduce more technologies in the laboratory. Reprod Biomed Online 2022;44(3):389–92.
[27] Allahbadia GN, Morimoto Y. Ovarian stimulation protocols. Springer; 2016.
[28] Glujovsky D, Pesce R, Miguens M, Sueldo CE, Lattes K, Ciapponi A. How effective are the non-conventional ovarian stimulation protocols in ART? A systematic review and meta-analysis. J Assist Reprod Genet 2020;37(12):2913–28.
[29] Mol BW, Bossuyt PM, Sunkara SK, Velasco JAG, Venetis C, Sakkas D, et al. Personalized ovarian stimulation for assisted reproductive technology: study design considerations to move from hype to added value for patients. Fertil Steril 2018;109(6):968–79.
[30] Doroftei B, Ilie OD, Anton N, Marcu OA. Scripcariu IS, Ilea C. A narrative review discussing the efficiency of personalized dosing algorithm of follitropin delta for ovarian stimulation and the reproductive and clinical outcomes. Diagnostics 2023;13(2):177.
[31] Haahr T, Esteves SC, Humaidan P. Individualized controlled ovarian stimulation in expected poor-responders: an update. Reprod Biol Endocrinol 2018;16:1–9.
[32] AlSaad R, Abd-Alrazaq A, Choucair F, Ahmed A, Aziz S, Sheikh J. Harnessing artificial intelligence to predict ovarian stimulation outcomes in *in vitro* fertilization: scoping review. J Med Internet Res 2024;26.
[33] Curchoe CL, Bormann CL. Artificial intelligence and machine learning for human reproduction and embryology presented at ASRM and ESHRE 2018. J Assist Reprod Genet 2019;36:591–600.
[34] 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 2021;11(5):743.
[35] Mann M, Kumar C, Zeng WF, Strauss MT. Artificial intelligence for proteomics and biomarker discovery. Cell Syst 2021;12(8):759–70.
[36] Zieliński K, Pukszta S, Mickiewicz M, Kotlarz M, Wygocki P, Zieleń M, et al. Personalized prediction of the secondary oocytes number after ovarian stimulation: a machine learning model based on clinical and genetic data. PLoS Comput Biol 2023;19(4):e1011020.
[37] Cesario A, D'Oria M, Bove F, Privitera G, Boškoski I, Pedicino D, et al. Personalized clinical phenotyping through systems medicine and artificial intelligence. J Pers Med 2021;11(4):265.
[38] Rezaeiye RD, Mehrara A, Pour AMA, Fallahi J, Forouhari S. Impact of various parameters as predictors of the success rate of *in vitro* fertilization. Int J Fertil Steril 2022;16(2):76.
[39] Martínez LC, Murria L, Valera MÁ, Cobo A, Meseguer M. Testing the ability of an artificial inTELligence (AI) algorithm in predicting implantation and ongoing pregnancy potential of vitrified-warmed blastocysts from a single image. Fertil Steril 2023;120(4) [Internet][cited 2024 Oct 20]e41–2. Available from, https://www.fertstert.org/article/S0015-0282(23)00909-3/abstract.
[40] Ozturk S. Selection of competent oocytes by morphological criteria for assisted reproductive technologies. Mol Reprod Dev 2020;87(10):1021–36.
[41] Hanassab S, Abbara A, Yeung AC, Voliotis M, Tsaneva-Atanasova K, Kelsey TW, et al. The prospect of artificial intelligence to personalize assisted reproductive technology. npj Digit Med 2024;7(1):55.
[42] Dias T.R., Cho C.L., Agarwal A. Sperm assessment: traditional approaches and their indicative value. *In vitro* fertilization: a textbook of current and emerging methods and devices. 2019;249–63.
[43] Marzano G, Chiriacò MS, Primiceri E, Dell'Aquila ME, Ramalho-Santos J, Zara V, et al. Sperm selection in assisted reproduction: a review of established methods and cutting-edge possibilities. Biotechnol Adv 2020;40:107498.
[44] You JB, McCallum C, Wang Y, Riordon J, Nosrati R, Sinton D. Machine learning for sperm selection. Nat Rev Urol 2021;18(7):387–403.
[45] Hicks SA, Andersen JM, Witczak O, Thambawita V, Halvorsen P, Hammer HL, et al. Machine learning-based analysis of sperm videos and participant data for male fertility prediction. Sci Rep 2019;9(1):16770.
[46] Spencer L, Fernando J, Akbaridoust F, Ackermann K, Nosrati R. Ensembled deep learning for the classification of human sperm head morphology. Adv Intell Syst 2022;4(10):2200111.
[47] Shahali S, Murshed M, Spencer L, Tunc O, Pisarevski L, Conceicao J, et al. Morphology classification of live unstained human sperm using ensemble deep learning. Adv Intell Syst 2024:2400141.
[48] Conti M, Franciosi F. Acquisition of oocyte competence to develop as an embryo: integrated nuclear and cytoplasmic events. Hum Reprod Update 2018;24(3):245–66.
[49] Lemseffer Y, Terret ME, Campillo C, Labrune E. Methods for assessing oocyte quality: a review of literature. Biomedicines 2022;10(9):2184.
[50] Balaban B, Keles I, Ebner T. Morphological assessment of oocyte quality. Man Oocyte Retr Prep Hum Assist Reprod 2022:85.
[51] Si K, Huang B, Jin L. Application of artificial intelligence in gametes and embryos selection. Hum Fertil 2023;26(4):757–77.
[52] Bhide P, Chan DY, Lanz D, Alqawasmeh O, Barry E, Baxter D, et al. Clinical effectiveness and safety of time-lapse imaging systems for embryo incubation and selection in *in-vitro* fertilisation treatment (TILT): a multicentre, three-parallel-group, double-blind, randomised controlled trial. Lancet 2024;404(10449):256–65.
[53] Buldo-Licciardi J, Large MJ, McCulloh DH, McCaffrey C, Grifo JA. Utilization of standardized preimplantation genetic testing for aneuploidy (PGT-A) via artificial intelligence (AI) technology is correlated with improved pregnancy outcomes in single thawed euploid embryo transfer (STEET) cycles. J Assist Reprod Genet 2023;40(2):289–99.
[54] Aydin B, Hudkova D, Halicigil C. Maximizing donor egg efficiency: artificial intelligence and genetically certified oocytes. Cryopreservation. In: Nagy ZP, Varghese AC, Agarwal A, editors. Assisted reproduction: a practitioner's guide to

methods, management and organization [Internet]. Cham: Springer International Publishing; 2024. p. 471–90. https://doi.org/10.1007/978-3-031-58214-1_48 [cited 2024 Nov 27]Available from.
[55] Celebi D, Omur AD, Akarsu SA. Celbis SC, Baser S. Artificial intelligence in gamete cell selection and semen microbiologic analysis. J Clin Vet Res 2022;2(2).
[56] Farías AFS, Sakkas D, Chavez-Badiola A, Ocali O, Mendizabal G, Valencia R, et al. Single-sperm motility analysis during ICSI using an artificial intelligence sperm identification software (SID) and correlation with morphology. Fertil Steril 2022; 118(4):e56–7.
[57] Letterie G. Artificial intelligence and assisted reproductive technologies: 2023. Ready for prime time? Or not. Fertil Steril 2023;120(1):32–7.
[58] Young ST, Tzeng WL, Kuo YL, Hsiao ML, Chiang SR. Real-time tracing of spermatozoa. IEEE Eng Med Biol Mag 1996;15(6):117–20 [Internet][cited 2024 Oct 20]Available from https://ieeexplore.ieee.org/abstract/document/544519/?casa_token=GpP9AUPYZ_IAAAAA:86t9dMCGNa5M003wdfi5aUrK28h06ylMzH2bqZ3J0z3jOcaP-bzEKv23-sMqpvYn1TznvcmW.
[59] Itoi F, Miyamoto T, Himaki T, Honnma H, Sano M, Ueda J. Importance of real-time measurement of sperm head morphology in intracytoplasmic sperm injection. Zygote 2022;30(1):9–16 [Internet][cited 2024 Oct 20]Available from https://www.cambridge.org/core/journals/zygote/article/importance-of-realtime-measurement-of-sperm-head-morphology-in-intracytoplasmic-sperm-injection/7C10CF2237C9970EFC132D38ECAAC11E.
[60] Feyeux M, Reignier A, Mocaer M, Lammers J, Meistermann D, Barrière P, et al. Development of automated annotation software for human embryo morphokinetics. Hum Reprod 2020;35(3):557–64.
[61] Berntsen J, Rimestad J, Lassen JT, Tran D, Kragh MF. Robust and generalizable embryo selection based on artificial intelligence and time-lapse image sequences. PLoS One 2022;17(2):e0262661.
[62] Harris BS, Bishop KC, Kuller JA, Alkilany S, Price TM. Preimplantation genetic testing: a review of current modalities. F S Rev 2021;2(1):43–56.
[63] Stankewicz T. Optimizing ivf by controlling for both embryonic aneuploidy and endometrial receptivity using genetic testing. University of Kent (United Kingdom; 2021.
[64] Kort J., Behr B. Traditional embryo morphology evaluation: from the zygote to the blastocyst stage. *In vitro* fertilization: a textbook of current and emerging methods and devices. 2019;493–504.
[65] Sciorio R, Meseguer M. Focus on time-lapse analysis: blastocyst collapse and morphometric assessment as new features of embryo viability. Reprod Biomed Online 2021;43(5):821–32.
[66] Rosenwaks Z, Handyside AH. Is preimplantation genetic testing for aneuploidy an essential tool for embryo selection or a costly 'add-on'of no clinical benefit? Fertil Steril 2018;110(3):351–2.
[67] Berntsen J, Rimestad J, Lassen JT, Tran D, Kragh MF. Robust and generalizable embryo selection based on artificial intelligence and time-lapse image sequences. PLoS One 2022;17(2):e0262661 [Internet][cited 2024 Nov 27]Available from, https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0262661.
[68] e Z ul Ishaq M, Raza S, Rehar H, Abadeen S, Hussain D, Naqvi RA, et al. Assisting the human embryo viability assessment by deep learning for *in vitro* fertilization. Mathematics 2023;11(9):2023.
[69] Dimitriadis I, Zaninovic N, Badiola AC, Bormann CL. Artificial intelligence in the embryology laboratory: a review. Reprod Biomed Online 2022;44(3):435–48.
[70] Stegmaier J, Amat F, Lemon WC, McDole K, Wan Y, Teodoro G, et al. Real-time three-dimensional cell segmentation in large-scale microscopy data of developing embryos. Dev Cell 2016;36(2):225–40 [Internet][cited 2024 Oct 20]Available from, https://www.cell.com/developmental-cell/fulltext/S1534-5807(15)00837-0.
[71] Lundin K, Park H. Time-lapse technology for embryo culture and selection. Ups J Med Sci 2020;125(2):77–84 [Internet][cited 2024 Oct 20]Available from, https://ujms.net/index.php/ujms/article/view/5629.
[72] Chavez-Badiola A, Flores-Saiffe-Farías A, Mendizabal-Ruiz G, Drakeley AJ, Cohen J. Embryo ranking intelligent classification algorithm (ERICA): artificial intelligence clinical assistant predicting embryo ploidy and implantation. Reprod Biomed Online 2020;41(4):585–93 [Internet][cited 2024 Oct 20]Available from https://www.sciencedirect.com/science/article/pii/S1472648320303734?casa_token=jM2SA9P-Ji8AAAAA:C8UFa-LeFSxiUZ37Ly1owL_ZAjDoQ5Jih_goblqsJq_NKiOe7MH5BSbWgMObLU6mYdhMNWaf.
[73] Ueno S, Berntsen J, Ito M, Okimura T, Kato K. Correlation between an annotation-free embryo scoring system based on deep learning and live birth/neonatal outcomes after single vitrified-warmed blastocyst transfer: a single-centre, large-cohort retrospective study. J Assist Reprod Genet 2022;39(9):2089–99 [Internet][cited 2024 Oct 20]Available from, https://link.springer.com/10.1007/s10815-022-02562-5.
[74] De Gheselle S, Jacques C, Chambost J, Blank C, Declerck K, De Croo I, et al. Machine learning for prediction of euploidy in human embryos: in search of the best-performing model and predictive features. Fertil Steril 2022;117(4):738–46 [Internet][cited 2024 Oct 20]Available from, https://www.sciencedirect.com/science/article/pii/S001502822102238X.
[75] Durai P. Quality control in the assisted reproductive technology laboratory. CRC Press; 2024.
[76] Fabozzi G, Cimadomo D, Maggiulli R, Vaiarelli A, Ubaldi FM, Rienzi L. Which key performance indicators are most effective in evaluating and managing an *in vitro* fertilization laboratory? Fertil Steril 2020;114(1):9–15.
[77] Ain QU, Nazir R, Nawaz A, Shahbaz H, Dilshad A, Mufti IU, et al. Machine Learning Approach towards Quality Assurance, Challenges and Possible Strategies in Laboratory Medicine. J Clin Transl Pathol 2024;4(2):76–87.
[78] Rahmani AM, Yousefpoor E, Yousefpoor MS, Mehmood Z, Haider A, Hosseinzadeh M, et al. Machine learning (ML) in medicine: review, applications, and challenges. Mathematics 2021;9(22):2970.
[79] Bormann CL, Curchoe CL, Thirumalaraju P, Kanakasabapathy MK, Gupta R, Pooniwala R, et al. Deep learning early warning system for embryo culture conditions and embryologist performance in the ART laboratory. J Assist Reprod Genet 2021;38(7):1641–6.
[80] Tamir S. Artificial intelligence in human reproduction: charting the ethical debate over AI in IVF. AI Ethics 2023;3(3):947–61.
[81] 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.
[82] Hammond ER, Morbeck DE. Tracking quality: can embryology key performance indicators be used to identify clinically relevant shifts in pregnancy rate? Hum Reprod 2019;34(1):37–43.
[83] tian Wang H, ping Hong P, yang Li H, Zhou W, Li T. Use of a new set of key performance indicators for evaluating the performance of an *in vitro* fertilization laboratory in which blastocyst culture and the freeze-all strategy are the primary treatment in patients with *in vitro* fertilization. J Int Med Res 2021;49(9):03000605211044364.
[84] Di Paola R, Cuccarollo A, Garzon S. Risk, safety, and outcome monitoring in the IVF clinic. Management of infertility. Elsevier; 2023. p. 397–404 [Internet][cited 2024 Oct 20]Available from, https://www.sciencedirect.com/science/article/pii/B9780323899079000089.
[85] Zaca C., Borini A., Coticchio G. Laboratory monitoring for embryo culture. Manual of embryo culture in human assisted reproduction [Internet]. 2021 [cited 2024];84. Available from: https://books.google.com/books?hl=en&lr=&id=a3IqEAAAQBAJ&oi=fnd&pg=PA84&dq=Quality+Control+and+Key+Performance+Indicators+Monitoring+in+IVF+Embryo+Culture+Conditions&ots=ShuiWM_MtI&sig=BhuV6RgiQBuLNmAjs5bheNbBDKA.
[86] Franco Jr JG, Petersen CG, Mauri AL, Vagnini LD, Renzi A, Petersen B, et al. Key performance indicators score (KPIs-score) based on clinical and laboratorial parameters can establish benchmarks for internal quality control in an ART program. JBRA Assist Reprod 2017;21(2):61 [Internet][cited 2024 Oct 20] Available from, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5473694/.
[87] Li D, Gao Y. Introduction of quality control and risk management in IVF laboratory. Qual Manag Assist Reprod Lab 2024:1–17.
[88] Doody K., Calhaz-Jorge C., Smeenk J. Quality data to assurance improve clinical of ART care practice: using. Assisted reproductive technology surveillance [Internet]. 2019 [cited 2024 Oct 20];4:69. Available from: https://books.google.com/books?hl=en&lr=&id=dIOWDwAAQBAJ&oi=fnd&pg=PA69&dq=Quality+Control+and+Key+Performance+Indicators+Monitoring+in+IVF+Continuous+Improvement&ots=8ocSTxGw2H&sig=gw71OQflBBkJw16WtFg6V82Vqqs.
[89] Cohen J, Alikani M, Gilligan A. Updated guidelines for setting up an assisted reproductive technology laboratory. Textbook of assisted reproductive techniques. CRC Press; 2023. p. 1–8.
[90] Passet-Wittig J, Bujard M. Medically assisted reproduction in developed countries: overview and societal challenges. Res Handb Sociol Fam 2021:417–38.
[91] Pavlovic ZJ, Jiang VS, Hariton E. Current applications of artificial intelligence in assisted reproductive technologies through the perspective of a patient's journey. Curr Opin Obstet Gynecol 2024;36(4):211–7.
[92] Zaninovic N, Elemento O, Rosenwaks Z. Artificial intelligence: its applications in reproductive medicine and the assisted reproductive technologies. Fertil Steril 2019;112(1):28–30.
[93] Chow DJX, Wijesinghe P, Dholakia K, Dunning KR. Does artificial intelligence have a role in the IVF clinic? Reprod Fertil 2021;2(3):C29–34.
[94] Health TLD. Enhancing the success of IVF with artificial intelligence. Lancet 2023;5. Digital health.
[95] Liang W, Tadesse GA, Ho D, Fei-Fei L, Zaharia M, Zhang C, et al. Advances, challenges and opportunities in creating data for trustworthy AI. Nat Mach Intell 2022;4(8):669–77 [Internet][cited 2024 Oct 20]Available from, https://www.nature.com/articles/s42256-022-00516-1.
[96] Afnan MAM, Rudin C, Conitzer V, Savulescu J, Mishra A, Liu Y, et al. Ethical implementation of artificial intelligence to select embryos in *in vitro* fertilization. In: Proceedings of the 2021 AAAI/ACM conference on AI, ethics, and society. ACM; 2021. p. 316–26 [Internet]. Virtual Event USA[cited 2024 Oct 20]Available from, https://dl.acm.org/doi/10.1145/3461702.3462589.
[97] Silva I, Soto M. Privacy-preserving data sharing in healthcare: an in-depth analysis of big data solutions and regulatory compliance. Int J Appl Health Care Anal 2022;7(1):14–23 [Internet][cited 2024 Oct 20]Available from, http://norislab.com/index.php/IJAHA/article/view/39.
[98] Panesar A. Precision health and artificial intelligence: with privacy, ethics, bias, health equity, best practices, and case studies [Internet]. Berkeley, CA: Apress; 2023 [cited 2024 Oct 20]. Available from, https://link.springer.com/10.1007/978-1-4842-9162-7.
[99] Frank E., Olaoye G. Privacy and data protection in AI-enabled healthcare systems. 2024 [cited 2024 Oct 20]; Available from: https://www.researchgate.net/profile/Edwin-Frank/publication/378287462_Privacy_and_data_protection_in_AI-enabled_healthcare_systems/links/65d0dc54476dd15fb343ff84/Privacy-and-data-protection-in-AI-enabled-healthcare-systems.pdf.
[100] GhoshRoy D, Alvi PA, Santosh KC. AI tools for assessing human fertility using risk factors: a state-of-the-art review. J Med Syst 2023;47(1):91 [Internet][cited 2024 Oct 20]Available from: https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1007/s10916-023-01983-8&casa_

token=NrqwKnfxLzkAAAAA:2cONbCFL6tXtn8EpGZ6GT37AIJEowqtRvKaynQJQ–MQPaQjiWaf29XmGJ37xoYViYZIXPI_TK4OHHo.
[101] De A, Saraf S, Mishra TK, Tripathy BK. Interpretation and visualization techniques in AI systems and applications. Explainable, interpretable, and transparent ai systems. CRC Press; 2024. p. 279–301 [Internet][citedOct 20]Available from https://w.w.w.taylorfrancis.com/chapters/edit/10.1201/9781003442509-16/interpretation-visualization-techniques-ai-systems-applications-arka-de-sameeksha-saraf-tusar-kanti-mishra-tripathy.
[102] Alolabi H, Aarthy CCJ. Ethical challenges presented by advanced artificial intelligence in diagnostics and treatment recommendations. J Empir Soc Sci Stud 2021;5(1):30–47 [Internet][cited 2024 Oct 20]Available from, https://publications.dlpress.org/index.php/jesss/article/view/31.