RESEARCH PAPER

A SWOT Analysis of Human Expertise and Machine Learning Techniques: A comprehensive study on Embryo Assessment

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ABSTRACT
Embryo screening is a imperative component of Assisted Reproductive Technology (ART) as it permits clinicians to pick out the embryo having the greatest potential of attaining pregnancy. Historically, embryologists examined embryos visually under a microscope. They looked at the shape of the embryo, how many cells it had and how quickly it was growing. While this method has been helpful, it relies on human interpretation which can lead to different results from different experts. Within the recent years, Artificial Intelligence (AI) and Machine Learning (ML) have lent a hand in making embryo screening more accurate and reliable. Large scale AI and ML can learn from more embryo images and videos obtaining critical details that might evade humans about the topic provided, we compare experts (human) vs. AI-based systems using SWOT analysis (Strengths, Weaknesses, Opportunities & Threats). Non-Machine human experts have experience, medical knowledge and ethical understanding. While AI provides quick, consistent results based on data. Both have some limitations. This paper demonstrates that human experts and AI can collaborate to produce better decisions. It also elucidates how explainable AI models and human-AI models can help to make ART reliable, safe, and useful for patients in the future.

Keywords: *Embryo Assessment; Assisted Reproductive Technology (ART); Artificial Intelligence (AI); Machine Learning (ML); IVF; SWOT Analysis; Explainable AI*
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1. INTRODUCTION

Embryo evaluation is a crucial component and is also one of the first steps in IVF, which has a profound effect on the probability of pregnancy success [1]. With the advent of the first successful IVF pregnancy in 1978 there has been An urgent need for precise selection of embryo quality aimed to optimize the increasing implantation rates and decreasing multiple pregnancies/multiple gestation [2]. The embryologists have been selecting an embryo to transfer based on appearance and development. These evaluations are based on manual examination under a microscope according to parameters including blastomere symmetry, cytoplasm fragmentation and cell number/multinucleation [3]. While this traditional manner of conducting research has been a successful model for many years, but has some flaws as well. There has been a huge debate of subjectivity in embryo grading as so much is dependent on the experience and skill of the embryologist and years served, hence both inter- as well intra–obsessive differences are seen when choosing or rating embryos. The evolution of reproductive science resulted in new technologies which permit a much more precise and uniform means of evaluating embryos. One of them, the time-lapse technique has substantially influenced embryology because it allows constant and non-invasive monitoring of developmental dynamics of an embryo. The so-called morpho kinetics has been established as a new discipline [4]. Morpho kinetics Morpho kinetics is a science that captures and evaluates the timing of specific early embryonic landmarks such as length of division intervals, blastocyst formation [5]. It can be employed for morpho kinetic algorithms, which would provide better prediction of viability of an embryo and its implantation potential [6]. But with the help of morpho kinetics, and other developments in embryo selection techniques, the subjectivity is still high as embryologists are humans who manually assess these data sets. The practical application effectiveness of these methods in choosing the best embryo is often impaired by human errors and fatigue as well as the bottleneck a single embryologist may have to process huge amount of data.

In the recent some years, AI and ML [7] have started to revolutionise this landscape providing a data driven

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approach in contrast with the traditional modes of assessment. First, these technologies use sophisticated computational algorithms that can be applied to analyze large collections, such as large data from high-definition images of an embryo, time-lapse video and patient information [8] up to the molecular level differences for identification of patterns associated with pregnancy/implant success. CNNs are among the deep learning techniques that have been successful in developing automatic embryo grading and extracting fine morphological and developmental details that could not be noticed by a human eye [9]. These models could generate a prediction of the score from the probability of embryo transfer that would result in a better and more consistent informed clinical decision. In addition, the use of AI in embryology can help to standardize and reproduce laboratory procedures, which was previously difficult with human evaluations [10]. A combination of different dataset (embryologic data, hormonal data and genetic information) can also be included in the ML and optimise treatment of each patient undergoing IVF, (11). The clinical IVF data have debate regarding protection, consent and disclosure. However, significant efforts will be necessary to validate models in a diverse patient population in different clinical context. Thus, rather than AI replacing human experience, it acts as a good support (as with planning) in Embryo assessment and IVF. In the above backdrop, it is important to consider the different shades of human and/automated embryo evaluation grading. Each of the methods [12] have their pros and cons, and potential. To conduct a systematic review and classify AI/ML methodologies utilized in Embryo Evaluation and Selection, in the context of IVF. This paper provides a critical, systematic and a newer review for the use of AI/ML methods in Embryo analysis and screening. We describe the biological and clinical context, review methodological approaches and give benchmarks, Highlight issues still to be resolved and propose a research agenda for the future. The paper has been organized in the following way, Section 2 addresses the clinical background; Section 3 includes the description of the methodology pipeline; Section 4 addresses the review of AI/ML techniques; Section 5 addresses the review of datasets and evaluation metrics; Section 6 addresses the comparative analysis; Section 7 discusses challenges; Section 8 addresses the future directions; Section 9 concludes.

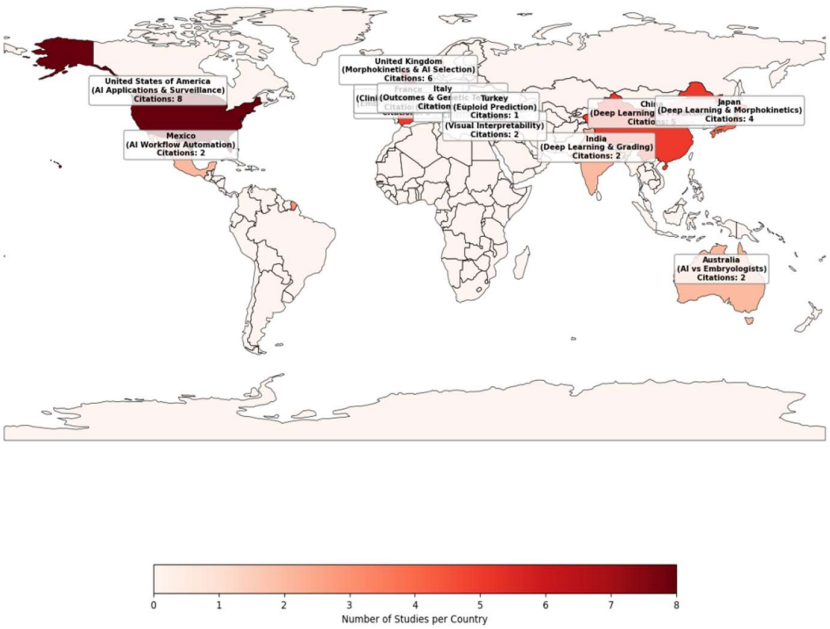

Fig 1: Global Distribution of ART and AI Research

2. Clinical Background and Embryology

Embryo evaluation is of crucial importance for IVF, especially to evaluate the quality and developmental capability of embryos prior to implantation. From the time of its introduction [13], embryologists have been making visual observations, mostly on morphology and cleavage rate of embryos to determine which will have the highest probability for becoming a pregnancy [14]. These "conventional" evaluation criteria evaluate the embryo at the microscopic level by assessing embryo structure and symmetry, blastomere number, and fragment rate [15]. Despite their use in clinical decision making for decades, such evaluations are subjective by nature and rely on the experience and interpretation of the embryologist, often

leading to inter-laboratory and intra-practitioner outcome differences. In the context of improving the accuracy of embryo evaluation and reproductive interventions, the limitations of manual embryo scoring [16] are becoming more apparent. Manual assessment is representation of a laborious and human-dependent process, also less repeatable, more subjective and included intra- and inter-individual planes variation; even the most skilled embryologist cannot be able to estimate correctly the implantation chance.

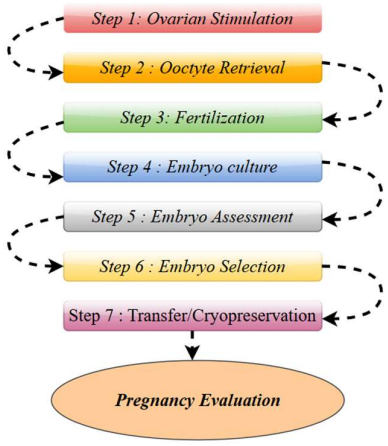

Fig 2: Flowchart of IVF Embryo assessment process

2.1 Conventional Morphological Assessment (Morphology, Morpho Kinetic)

The traditional embryo evaluation depends on the expertise of trained embryologists who look at embryos under light microscopy at set growth intervals - usually Day 1 (zygote), Day 2-3 (cleavage stage), and Day 5-6 (blastocyst stage) [17,77]. A quantified set of morphological criteria are used to describe the quality of embryos at each time point. During cleavage, evaluation of cell number, symmetry, percentage fragmentation, and multinucleation are determined by the Istanbul Consensus criteria. Gardner-Schoolcraft grading system is universally used at the blastocyst stage, where the degree of expansion (1-6), morphology of inner cell mass (ICM) (A- C) and morphology of trophectoderm (TE) (A- C) are scored [18]. The most important morphological criteria at every stage of development are shown in Table 1 below. These criteria have been formulated over decades of retrospective clinical experience, and embodies an effort to codify an otherwise subjective visual examination process. In spite of this standardisation attempt, research has on a consistent basis shown a significant inter-laboratory and inter-observer variability [19]. Cleavage stage grading intra-class correlation coefficients of 0.43-0.71 [20] and Storr et al. reported that the concordance of the grade of blastocyst ICM was only 67% among five experienced centres [21].

Table 1: Recent Advances in Artificial Intelligence for Embryo and Gamete Selection in IVF

Day	Stage	Optimal Cell No.	Positive Morphology Indicators	Rejection Criteria
Day 1 [22]	Zygote	2PN, 2PB present	Regular PN size; equal PB	Abnormal PN; >2PN
Day 2 [23]	Cleavage	4 cells; <10% frag	Equal blastomeres; intact ZP	Multinucleation; arrest
Day 3 [24]	Cleavage	8 cells; <10% frag	Symmetric; Grade A/B	Fragmentation >25%; arrest
Day 4 [25]	Morula	Compaction initiated	Full compaction; delineated ICM	Failed compaction
Day 5 [26]	Blastocyst	4AA–4AB ideal	Expanded; distinct ICM/TE	Grade CC; collapsed
Day 6 [27]	Blastocyst	Expanded/hatching	Hatching; good ICM/TE	Late formation; poor grade

Note: ZP = zona pellucida; ICM = inner cell mass; PN = pronuclei; PB = polar body; frag = fragmentation. Adapted from Istanbul Consensus (Alpha/ESHRE, 2011) and Gardner & Schoolcraft (1999).

The shortcomings of the static morphological evaluation have led to the beginning of a time-lapse incubation method of monitoring embryo development continuously, non-invasively, between fertilisation and blastocyst [28]. Time-lapse systems, such as the EmbryoScope (Vitrolife), Primo Vision (Vitrolife), and Miri TL (Esco Medical) take images at intervals of 5-20 minutes, producing extensive morphokinetic data of hundreds or thousands of images per embryo [29]. These time data parameters that cannot be measured using standard single-point assessment are now increasingly being recognised as potent predictors of developmental competence, euploidy, and implantation potential [30]. Several morphokinetic parameters that can be determined using time-lapse imaging, such as time to

first cleavage (t2), synchrony of the second cleavage (s2), time to blastocyst formation (tB), and compaction timing (tM) have been linked to blastocyst formation rates, euploidy, and live birth in various clinical studies [31]. The full picture of these parameters is given in Table 5 (in Section B). But the sheer amount and difficulty of time-lapse data have presented a new informatics problem: the manual analysis of full morphokinetic trajectories of all embryos within a population is beyond the cognitive abilities of even the most expert embryologist [32]. This shortcoming is the main driving force behind the usage of machine learning for embryo evaluation and assesment.

2.2 The weaknesses of Traditional Morphological Grading

There is no universal standardisation of morphological grading systems across different clinics. Minimum standards were established in the Istanbul consensus (2011) and later in the ESHRE guidelines, but implementation is diverse [33]. The meta-analyses have shown that morphological grading only explains the variability in the results of implantation by a factor of about 20-30 percent, reflecting the limited predictive capacity of morphological grading [34]. The inter-observer κ coefficients of the blastocyst grading are usually of the range of 0.35-0.65 which indicates moderate to fair agreement- not sufficient to make high-stakes clinical decisions [35].

2.3 Time-Lapse Technology and Morphokinetics

Time-lapse systems also capture the image of embryos in intervals of 5-20 minutes, resulting in the creation of the annotated videos on which morphokinetic variables are measured: time to 2 cells (t2), time to 3 cells (t3), time to 5 cells (t5), time to compaction (tM), time to blastulation onset (tSB), time to expanded blastocyst (Aneuploidy and bad results are linked with abnormal division events - multinucleation, direct cleavage, reverse cleavage. Morphokinetics are weakly-moderately associated with implantation (AUC 0.60 -0.72 alone) but their predictive ability is greatly increased when coupled with AI-guided image analysis [36].

3. Emergence of artificial intelligence (AI) and machine learning (ML) in embryo selection

Artificial intelligence (AI) and machine learning (ML) in embryo selection represent a revolutionary turning point for ART [49]. As the field of genetic medicine evolves, AI and ML are perceived as possible answers to many conventional embryo assessment limitations. In contrast to the visual and interpretive factors or the ongoing assessment of human reviews, AI systems use computational models comprising large dataset containing embryo images [174], time-lapse videos as well as genetic and metabolic data [175] in order to quantify an embryo's viability and capabiltiy for implantation rather than relying on observer-dependent qualitative assessments.

The application of AI for embryo selection was initiated with the development of computer vision and deep learning algorithms which could identify morphological and morpho kinetic markers associated with successful implantation [50]. Deep convolutional neural networks (CNNs) [176], a subset of deep learning, have shown considerable promise for performing the automatic recognition and classification of embryo images according to their developmental quality [51]. As they are trained on thousands of labelled embryo data sets, these algorithms can discern subtle patterns and features that an experienced embryologist may not even be aware exist. AI models, for instance, can evaluate timing of cell divisions and tracking of embryo development in the form of blastocyst expansion and inner cell mass formation to develop implantation probability scores - effectively assisting a clinician in deciding which embryo is more likely to succeed [177]. You would also need to know that machine learning is more than merely analysing images [178]. ML can create a multi-dimensional profile (demographics, hormonal status, ovarian stimulation response and embryology data) around patients' profiles through predictive modelling [52]. This structure of the two composites enables the model creation for example one able to predict not only embryo quality but also probability for a given patient to get pregnant. Evidence-based approaches enable knowledge-based decision making, and may also help avoid unnecessary IVF cycles through trial-and-error [53,54]. Also, the AI/embryo selection process is standardized. They inherently surpass the barriers posed by subjectivity and are capable of producing more consistent readings across labs and examiners than those provided by manual readouts [78]. The increased standardization might improve the clinical utility and prevent provider- or site-specific bias introduced by human interpretation influenced by anything but simple error with any on the Indel-consensus calls. Multiple commercialized AI systems exist, and are being implemented in ART centres around the world [179], attracting attention with claims of promising enhancements on implantation and pregnancy rates [180].

However, there are some challenges in utilizing AI technology in reproductive medicine [181]. The private nature of data, leading to ethical concerns about the AI models [182] and challenges in explaining AI-based clinical decisions are all key issues required to be addressed before routine automated [clinical] usage. Together with type of AI adopted, generalizability of AI is also regulated by quality and diversity of training data which needs to reflect diverse population as well as laboratory protocols and imaging devices used in study [4]. While all these points are subtle forms of ethical failure, the evolution and deployment of both AI and ML technologies in embryo selection nevertheless represents a radical shift towards personalized, targeted efficient reproductive healthcare. The cooperation between human experience with AI in evolving technology can strengthen embryo evaluation (increasing IVF success rate) [183].

Table 3 summarizes the literature overview on application of Artificial intelligence (AI) in embryonic and gamete selection in IVF. The research emphasizes the comparisons between standard depersonalized embryologist evaluations and AI-based embryo evaluation, generating interpretable and explainable machine learning models as well further investigating to more sophisticated methods in ML such as reinforcement learning model for predicting of embryos. Embryo selection, potential implantation, prediction of live birth and short term miscarriage risk represent the main endpoints. Datasets comprise clinical ART records, time-lapse imaging and static images of embryos and published reports. There are other types of reinforcement learning algorithms. AI was consistently demonstrated to enhance the predictive performance, in addition to homogenising embryo evaluation and supporting clinical judgment [184]. A key thrust with explainable, ethically-used AI is the need for transparency and clinicians' trust in such systems.. Obtained collectively, these reports elucidate the narrowing use of AI in improving embryo and gamete selection, ART optimization as well as personalized reproductive medicine.

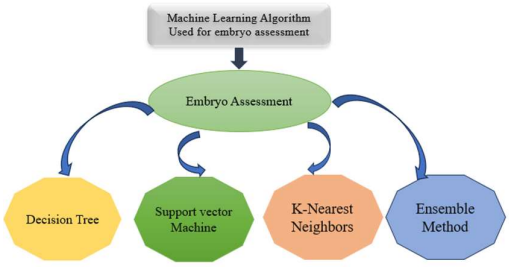

Fig 3: Machine learning models for embryo assessment and selection in IVF

Table 2: Recent Advances in Artificial Intelligence for Embryo and Gamete Selection in IVF

Study	Aims of Study	Outcomes of Interest	Dataset	Methods	Results
Salih et al. (2023) [55]	To compare AI-based embryo selection with embryologist assessment.	Accuracy of embryo selection, clinical outcomes.	Published studies and clinical reports.	Systematic review.	AI showed comparable or slightly improved selection accuracy, though human oversight remains critical.
Afnan et al. (2021) [56]	To advocate for interpretable AI rather than black-box models in embryo selection.	Transparency, ethical implementation, decision accuracy.	Literature and case examples.	Conceptual and ethical analysis.	Interpretable AI ensures ethical, accountable embryo selection without sacrificing predictive performance.
Glatstein et al. (2023) [578]	To review emerging technologies and methods in embryo selection.	Clinical success, embryo viability prediction.	Literature review of ART studies.	Narrative review.	AI, time-lapse imaging, and morphokinetic analysis are advancing embryo selection and personalized ART strategies.
Lee et al. (2024) [58]	To trace AI embryo selection development from black-box to explainable models.	Accuracy, interpretability, clinical adoption.	Historical studies and AI model reports.	Literature review.	Transition to glass-box AI improves transparency and clinician trust while maintaining predictive power.
Merican et al. (2021) [59]	To review machine learning methods for morphology-based embryo selection.	Embryo viability prediction.	Published clinical and imaging datasets.	Literature review of ML approaches.	ML models improve prediction of embryo viability based on morphology, though integration into practice varies.

Giscard d'Estaing et al. (2021) [60]	To develop a machine learning system that uses reinforcement learning for fate of an embryo prediction.	Embryo viability and implantation potential.	ART clinic datasets with outcome tracking.	Reinforcement learning-based AI model.	ML system predicted embryo outcomes accurately and adapted over time with reinforcement learning.
Afnan et al. (2021, AAAI/ACM) [61]	To discuss ethical AI implementation in embryo selection.	Ethical compliance, transparency, patient outcomes.	Literature and case studies.	Ethical and policy framework analysis.	Guidelines emphasize explainable AI, patient autonomy, and responsible clinical integration.
Chavez-Badiola et al. (2024) [62]	To predict first-trimester pregnancy loss using AI on static embryo images.	Early pregnancy loss prediction.	Static embryo image datasets.	AI image analysis and predictive modelling.	AI accurately predicted first-trimester loss, offering potential non-invasive embryo assessment.
Si et al. (2023) [63]	To review AI applications in gamete and embryo selection.	Gamete/embryo quality, selection accuracy.	Literature review of ART studies.	Narrative review of AI approaches.	AI helps choose better gametes and embryos, which make the success of IVF procedures higher.

3.1. Overview of AI models used (CNNs, deep learning, computer vision systems)

ML and AI have been transforming ART, offering more objective, data-driven, reproducible ways for quality assessment of the embryo [40] compared with traditional morphological evaluation [97]. The standard morphological and kinematic assessment which forms the cornerstone of fertility study guidelines are limited by intrinsic personal subjective analysis incorporating inter observer bias. In contrast, AI-based computational models [52] have employed sound algorithms to process a large number of embryo images, videos and clinical characteristics for the prediction of implantation potential and embryonic development with a high accuracy. Among the different artificial intelligence methods, CNNs (Convolutional Neural Networks) have emerged as the most powerful architectures for automation and improvement of embryo selection in deep learning-based computer vision systems [50]. The majority of the AI applications in embryo assessment leverage convolutional neural network (CNN) as their core [51]. It is suggested that these networks can process visual information and learn the meaningful patterns contained in images on their own (in an unsupervised fashion). For the embryo selection task, CNNs are trained over tens of thousands of annotated embryo image each with a known implantation/developmental outcome — to identify complex visual features pertaining to embryonic fitness [41]. CNNs do so via successive convolutional and pooling layers that disentangle morphological complexity including but not limited to cell symmetry, cell fragmentation, blastocyst expansion and inner cell mass Retrieved on Oct 2023 [42]. Once the model is trained however it can then be applied to score new images of embryos returning a number (or ranking) representing the probability for successful implantation. This protocol offers an objective, human-scoring free method and also provides a scalable decision across numerous labs. Similar to CNNs, other deep learning models share a close relationship in the context of Embryo Evaluation using various types of data [43]. Machine learning Deep learning – a class of machine learning where artificial neural networks with multiple hidden layers are used to analyse and learn from high-dimensional datasets [44]. These models can incorporate visual features from time-lapse imaging, but in ART they may also factor in non-visual information such as patient age, ovarian stimulation parameters and previous IVF treatment outcomes [45]. All of these data combined are also used to build very accurate predictive models (using machine (Deep) learning algorithms) for implantation potential, chromosomal normality and even likelihood of a live birth. Embryo culture offers a, dynamic aspect of embryogenesis is also being considered and recently RNN has been applied to interpret morpho kinetic patterns [46].

Computer vision systems (a wider class that includes both CNNs, and also AI based imaging methods) can be used to perform automatic image recognition and analysis in embryology labs [50]. These systems aim to mimic and improve our perception because they process data using methods such as image segmentation, pattern recognition and object detection [79]. Using the assessment of embryos as an example, computer vision algorithms are able to extract embryo developmental processes (i.e. pronuclear fading, cell division and expansion of blastocyst) automatically without human annotation [80]. This automation not only leads to significant time savings, but also guarantees that we can measure every parameter

of development in a completely reproducible and accurate manner. Logging in all the critical points, eventually computer vision technologies can be deployed inside time-lapse incubators for live embryo analysis and data are fed back into AI models that re-evaluate them.

There exist already several AI-based platforms, which have been optimized and validated for clinical use-cases with work-flows (for example Embryoscope, Life Whisperer, Ivy AI, ERICA (Embryo Ranking Intelligent Classification Algorithm) [98]. Such applications generally utilize CNNs and deep learning models to rank the embryos based on morphological and morpho kinetic measures, providing objective data for clinicians as an aid of embryo selection [81]. Morphologic grading of oocytes without AI can provide similar or better predictive outcomes compared to those noted above by embryologists with expertise [82].

But such AI models perform depending on the quality, diversity and quantity of the data in which they were trained [185]. If the model is trained on a smaller & homogeneous dataset, biased or less generalizable results can be achieved [186]. The "black box" of deep learning, meaning the fact that there is little transparency regarding why one prediction versus another came about due to an algorithm, is also clearly a problem from the standpoint of clinical transparency and trust [187]. However, this sort of restrictions the AI model representations (CNNs and computer vision in general) are just starting to take their baby steps forward but in theory they cast a shadow that eventually these future applications of form evaluation will transform into an objective scientific standardized process which with time can both shape & stabilize by data.

From reproductive medicine to the seamless integration of AI and ML models with embryo scoring and selection, the landscape is undergoing unprecedented change.The fusion of AI and ML with embryo scoring and selection marks a revolutionary shift in reproductive medicine. [188].

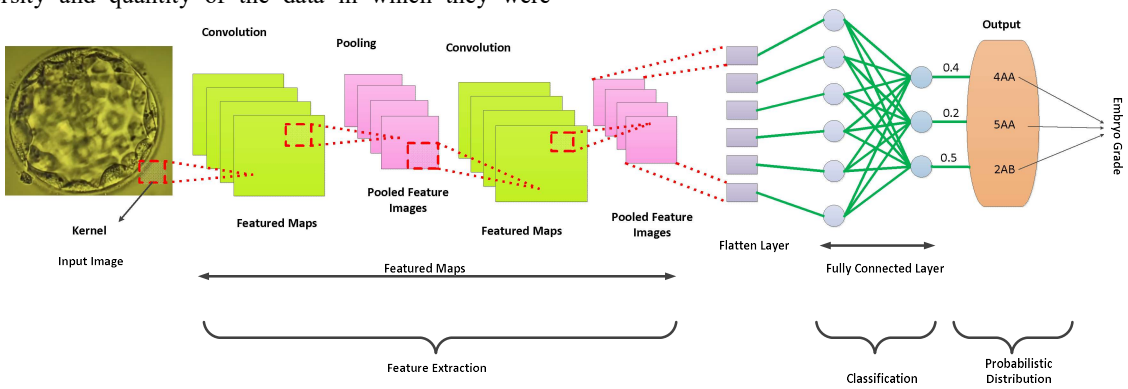

Figure 4: Architecture of a typical convolutional neural network (CNN) for Embryo assessment.

Table 3: Deep Learning and Machine Learning Approaches for Embryo Evaluation and Prediction in Assisted Reproductive Technology

Study	Aims of Study	Outcomes of Interest	Dataset	AI Methods	Results
Chavez-Badiola et al. (2020) [83]	To predict pregnancy outcomes after transferring embryo, image feature extraction and machine learning were used.	Prediction accuracy of positive pregnancy tests.	Embryo images post-transfer.	Machine learning with image feature extraction.	High accuracy was achieved in predicting whether the embryo will successfully implant.
Ishaq et al. (2023) [84]	To assist embryo viability assessment using deep learning.	Classification accuracy for viable vs. non-viable embryos.	IVF embryo image dataset.	Convolutional neural networks (CNN).	Model outperformed manual grading with higher objectivity.

Bormann et al. (2020) [85]	To evaluate objectivity and consistency of automated embryo assessments.	Agreement rate between AI and embryologists.	Clinical embryo image dataset.	Deep neural networks (DNN).	High consistency achieved, reducing inter-observer variability.
Kalatehjari et al. (2025) [86]	To develop DL models for assessing human embryo quality.	Embryo quality grading accuracy.	IVF laboratory datasets.	Deep learning (DL) models.	Reliable embryo grading with improved accuracy over manual scoring.
Berman et al. (2023) [87]	To systematically review DL for embryo evaluation in time-lapse imaging.	Diagnostic test accuracy of DL models.	Review of published time-lapse datasets.	Deep learning meta-analysis.	Reported significant accuracy and reproducibility improvements.
Attallah et al. (2020) [88]	To automate detection of embryonic neurodevelopmental disorders.	Early identification of neurodevelopmental anomalies.	Embryo neurodevelopmental images.	Deep learning (DL) and CNN models.	High detection rates for early-stage disorders.
Kanakasabapathy et al. (2020) [89]	To predict developmental outcome from single time-point embryo images.	Cleavage-stage developmental success prediction.	Time-point embryo images.	Deep learning with image-based models.	Accurate early-stage developmental forecasting.
Kalyani & Deshpande (2024) [90]	To predict blastocyst formation using time-lapse images.	Blastocyst formation rate prediction.	Cleavage-stage embryo time-lapse images.	CNN-based deep learning.	Outperformed traditional morphological methods.
Liao et al. (2024) [91]	To develop a clinical consensus-compliant DL model for early embryo evaluation.	Quantitative evaluation of early embryonic development.	Optical microscope images.	CNN and regression-based DL model.	Provided quantitative, standardized embryo assessment metrics.
Mapstone & Plusa (2025) [92]	To explore ML methods for image classification in developmental biology.	Classification accuracy and interpretability.	Developmental biology and clinical embryo image datasets.	Machine learning classifiers.	ML improved classification and visualization of developmental stages.
Boucret et al. (2025) [93	To design a DL model for embryo selection using matched time-lapse images.	Selection accuracy of high-quality embryos.	Time-lapse videos of matched embryos.	Deep learning (DL) CNN.	Significantly improved embryo selection consistency.
Shobha et al. (2022) [94]	To automate embryo classification and evaluation using DL.	Classification accuracy and automation efficiency.	Embryo datasets from IVF centers.	CNN and hybrid DL models.	Automated system achieved comparable accuracy to

					experts.
Vaidya et al. (2021) [95]	To predict viable embryos and automate grading using DL.	Time-series prediction of viability.	Time-lapse embryo images.	Recurrent neural networks (RNN).	Model accurately predicted viable embryos over time.
Sharma et al. (2025) [96]	To forecast embryo development using time-lapse videos.	Developmental outcome forecasting accuracy.	IVF time-lapse embryo datasets.	CNN-LSTM hybrid deep learning.	High predictive accuracy for embryo developmenta l stages.

This Technical table 6 aims to summarize relevant studies and articles related to the use of machine learning (ML) and deep learning (DL) for embryo quality assessment and prediction in ART. These studies illustrate how, as time goes on and imaging and laboratory techniques become more developed, the practice of AI algorithms with image and time-lapse analysis is pushing our grading ability for embryo quality, viability prediction and development forecasting. CNN, RNN and hybrid types of models could surpass classical morphological analysis. Databases will contain both normal and time-lapse embryo images, and appropriate for individual or translational predictions. In conclusion, the outcome indicates that artificial intelligence is capable to increase the predictive accuracy of FET while lowering any possible human bias and ensure reproducibility in embryo selection. The development of ethical, explainable and clinically relevant reproductive medicine sub-jects is also prioritized by the relevant, interpret-table and consensus-based AI systems. Together, these studies highlight AI-powered applications for precision embryo selection and optimization of IVF.

3.2 Machine learning pipeline for embryo assessment

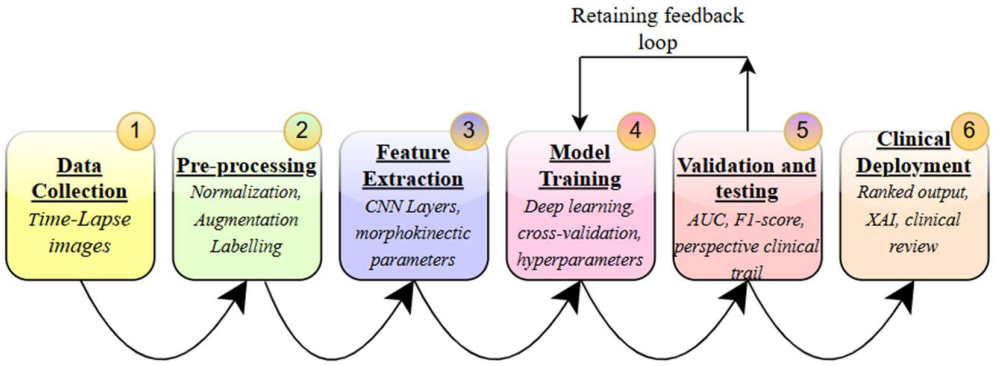

Figure 5: Machine Learning pipeline for Embryo assessment.

3.2.1 Data collection and preprocessing

Data collection and preprocessing is the core of any typical embryo assessment machine-learning (ML) or artificial intelligence (AI) pipeline [189]. In IVF, data are the raw material through which algorithms learn to recognize and classify data as well predict quality or implantation potential of embryos [190]. The details, variety and accuracy of data being collected are directly related to the performance and reliability AI models [191]. These include images, time-lapse videos and omic data (genomic, transcriptomic, proteomic or metabolomic profiles), which are based on three main approaches for embryo selection,[99]. As the two techniques yield complementary information regarding embryo morphology and development as well as molecular health, their application provides a more comprehensive, multidimensional assessment of the embryo [192]. Dense datatypes for AI-based embryo assessment are imported as static images, employing bright-field or differential interference contrast (DIC) microscopy [193]. We are using image stack cross-sections of embryos transitioning from Zygote to Blastocysts that previously served as visual-input to Convolutional Neural Networks (CNNs) [9] and/or other computer vision architectures. To learn, however, you will require enormous datasets with images annotated against endpoints such as implantation rate, percent of pregnancies and live births. Images are pre-processed by a series of steps such as normalization, noise removal, contrast enhancement and cropping from useless back round areas. Not only will this normalise the input data, but it will be used to coerce the models. to learn only those biologically relevant features like those of the blastomere morphology, cleavage patterns, and the trophectoderm compaction.

Besides static imaging, time-lapse videos are valuable data sets that can be provided for an ML model. Time-lapse

imaging systems Capture the development of embryos continuously at increasingly close time intervals, and produce high resolution video datasets for morpho kinetic analysis [194]. It can be particularly useful for training deep learning, and recurrent neural network (RNN) models, and videos can be recorded to incorporate that information.Videos can be recorded to include that information, and can be particularly useful for training deep learning and recurrent neural network (RNN) models. Some of which can process sequential data to detect temporal patterns to describe something like normal embryogenesis [195]. After a such time-lapsed data are then fed through a set of preprocessing operations (frame extraction, temporal synchronization, feature labelling), etc, to get to a series of disjoint frames. These types of preprocessing operations (frame extraction, temporal synchronization, etc. labelling features) produce a series of disjoint frames. AI-based modelling. Some developmental phases like pronuclear fading, cleavage time periods and blastocyst development are frequently labelled manually or semi-automatically in order to direct the learning process of the model. Data augmentation When there is data that is limited, techniques such as rotation, flipping, scaling are also applied to broaden the diversity of data sets and to enable a decrease in overfitting. limited number of videos available [196].

Omics data over and above morphological and morpho kinetic information have recently become an advanced level of Information complementary to analysing embryos using artificial intelligence [197]. The use of omics technology, such as genomics, transcriptomics, metagenomics, and metabolomics, as tools to advance drug delivery presents exciting prospects. The molecular fingerprint of embryos is revealed in the expression of genes, the synthesis of proteins and products of the biochemical reactions in the organism and is termed a proteomics and a metabolomics respectively. Information about the metabolic activities could be assumed [198]. For instance, culture media from embryos could be used for the non-invasive metabolome profiling that would reveal. the biochemical health status of the embryo; likewise, transcriptomic analysis can discover amounts of expression of genes associated with biochemical health conditions of the embryo. developmental competence [199].. The association of these datasets with continuous imaging and morphokinetic data could guide ML models to the building of multimodal frameworks able to link visual observations and molecular indicators of embryo viability [200]. Nonetheless, just like in the case of image inputs, it is challenging to preprocess omics data which involves several steps such as normalization, dimensionality reduction (for instance through feature selection), and scaling to bring the combined inputs into a compatible format [201].

Pre-processing concerns involve data quality issues including, but are not limited to: class imbalance, missing data, and heterogeneity of laboratory protocol [202]. The dataset is augmented to be more robust and training a generalized model. Furthermore, it is paramount to curate the data properly so that there are no mistakes and biased samples that can impact model prediction [118]. Since embryo information are sensitive and patient specific, preprocessing also have to follow ethical transforming procedures such as data anonymization while the data should be safely handled.

The first step and most critical one is data collection and processing which needs to be accurate for AI-based embryo evaluation [100]. The researchers are ensuring that meaningful correlations are learnt by machine learning models that can help predict an embryo's success of a pregnancy. potential of creating curated datasets from raw images, videos, and/or omics expression profiles. The integration of visual, temporal and molecular data is now allowing multidimensional analysis embryos in a way that is a step forward for personalized precision evidence-based reproductive health care.

3.2.2 Model training, validation, and integration into IVF workflows

The success of the use of machine learning (ML) and artificial intelligence (AI) for embryo assessment relies not only on good data, but also on well-validated model training [76]. Model training is the method AIML algorithms learn to understand patterns in data and make predictions which correlates with labelled outputs. In ART, layers of AI models have been trained using various categories of deep learning architectures (Convolutional Neural Networks in images and time-lapse videos) with datasets containing clinical outcomes (e.g. implantation-related success or live birth) from some embryos [101]. In this phase, the model is trained through iterative optimization of its inner parameters to minimize the prediction error and to learn complex relationships between morphological/morpho kinetic and omics factors and embryo viability [38]. The goal is to be able to generalize these learned patterns for new and unseen embryos, performing at a high rate with accuracy. Validation is critical to confirming generalization of trained models beyond the training dataset and avoiding overfitting when a model effectively memorizes reads by crushing, but performs poorly on other data [119]. Generally speaking, the dataset splits into three: a training set, validation set and test set. This part is used as a training dataset to derive the parameters of model fitting, while this piece acts as a validation set in hyper-parameter tuning phase and analyzing performances intermediate for the orders these data would be serving for testing conclusive accuracy for new observations. Performance: Accuracy, Precision, recall value, F1 score and AUC (ROC area) are very basic categories of cross-validation (k-fold cross validation for example) to give a more stable model which acts most efficiently with limited data.

Table 4: summarises the principal evaluation metrics used across reviewed studies.

Metric	Formula / Description	Used In
AUC-ROC	Area under ROC curve; ideal = 1.0	Classification tasks
Sensitivity (Recall)	TP / (TP + FN)	Live-birth/implantation prediction
Specificity	TN / (TN + FP)	Aneuploid embryo rejection
Intersection over Union	$\|A \cap B\| / \|A \cup B\|$	Segmentation quality
Mean Absolute Error	Avg |predicted – actual|	Developmental stage timing
Pearson Correlation (r)	$Cov(X,Y) / (\sigma X \cdot \sigma Y)$	Ranking model agreement
F1-Score	$2 \cdot (P \cdot R) / (P+R)$	Imbalanced class assessment

Yes, additional validation of the model using independent benchmark datasets at multiple other clinical sites provides confidence that the algorithm is generalizable across lab environment conditions, patient populations and imaging devices [111]. Therefore, the trained and validated AI models should be fair enough to integrate into IVF laboratory workflow without replacing existing clinical practices but facilitating them [101,102,103,104]. The different algorithms or systems based on AI could be integrated in the time-lapse incubators themselves or they could be created as independent software, providing real time embryo evaluation and grading.

Table 5: AI-Driven Workflow Optimization, Predictive Modelling, and Automation in IVF and Embryo Transfer

Study	Aims of Study	Outcomes of Interest	Dataset	AI Methods	Results
Letterie et al. (2022) [101]	To develop an AI platform to optimize workflow during ovarian stimulation and IVF.	Efficiency, prediction of IVF outcomes.	Clinical IVF cycle data.	Machine learning predictive algorithms.	Improved workflow efficiency and enhanced prediction accuracy for pregnancy outcomes.
Sergeev et al. (2024) [102]	To design a neural network pipeline for IVF lab quality management.	Quality assurance, laboratory process optimization.	IVF lab operational data.	Neural network models.	Improved consistency and reduced human error in lab quality management.
Sergeev & Diakova (2024) [103]	To propose a KPI-based framework for IVF pregnancy prediction models.	Model accuracy, key performance evaluation.	Multi-center IVF datasets.	ML-based KPI framework.	Demonstrated reliable prediction of pregnancy outcomes through data-driven KPIs.
Wygocki (2024) [104]	To validate AI integration in IVF from concept to clinical implementation.	Clinical validation of AI-based systems.	IVF clinical records.	AI-based decision support systems.	Enhanced embryo selection efficiency and clinical reproducibility.
Cimadomo et al. (2023) [105]	To validate a DL-based embryo grading system during PGT-A cycles.	Automation accuracy, grading reliability.	Embryo images from PGT-A cycles.	Deep learning CNN model.	Pre-clinical validation achieved with consistent grading accuracy.
Khoshkangini et al. (2024) [106]	To optimize IVF environments using AI-driven modeling.	Environmental and outcome optimization.	Environmental and clinical data.	AI optimization algorithms.	Demonstrated improved IVF culture conditions and success rates.
Rajendran et al. (2025) [107]	To develop a foundational model trained on large-scale embryo images.	Prediction of embryo development and success.	18 million time-lapse images.	Foundational deep learning model.	Achieved state-of-the-art prediction and generalizability across IVF datasets.
Zhu et al. (2025a) [108]	To predict the outcomes in patients with endometriosis using	Live birth prediction accuracy.	Patient and clinical data post-transfer.	Machine learning algorithms.	Model successfully predicted live birth outcomes with high accuracy.

	ML.				
Chavez-Badiola et al. (2025) [109]	To automate day-0 IVF laboratory workflow with AI.	Workflow automation, clinical outcome validation.	IVF lab and clinical workflow data.	Multi-stage AI workflow model.	Validated first clinical pregnancies through AI-driven automation.
Zhu et al. (2025b) [110]	To develop ML models predicting live birth in IVF/ICSI with PCOS patients.	Live birth success prediction.	Clinical IVF datasets with PCOS.	Machine learning regression models.	Accurate model predictions improved decision-making in IVF/ICSI treatments.

Table 7 summarizes literature that analyses the application types of AI on IVF; specifically, such as optimization of IVF workflow, embryo selection, and prediction of live birth. They performed ML, NN and DL algorithms above those for complex automated clinical steps in IVF correlated with ovarian stimulation as well as embryo grading/lab QC. And larger data sets such as Rajendran et al. s∼1.8×106 time-lapse imaging represents a significant generalization where both the training and predictive model differ. AI platforms assisted precision patients care during IVF clinical practice and improved the laboratory operations mood. Results around live birth outcomes in the endometriosis then PCOS cohort stood out especially, while studies showcasing automation of workflow tended to discuss real-world external clinical validation. They collectively suggest how AI might change the business of IVF by making it more efficient, and achieving greater accuracy and success rates by way of automation, prediction and optimized quality control.

Table 8: Overview of Commercial AI/ML Platforms for Clinical Embryo Evaluation

Tool	Developer	Method	Output	Key Evidence / Notes
iDAScore v1.0/2.0 [47]	Vitrolife (SE)	Deep CNN on time-lapse	Viability score 1–10	CE-marked; multicentre EU validation; AUC 0.65 vs 0.59 (Gardner)
KIDScore D3/D5 [48]	Vitrolife (SE)	Morphokinetic algorithm	Ranked viability score	Prospective RCT data; Day 3 and Day 5 versions
EEVA System [54]	CooperSurgical (US)	Early cleavage time-lapse	Developmental probability	First FDA-cleared AI embryo tool (2013)
Life Whisperer [64]	Presagen (AU)	Deep learning image only	Implantation likelihood	Blinded prospective study; cloud-based; 76% euploidy accuracy
Igenomix AI [65]	Igenomix (ES)	Genomics + morphology	Euploidy prediction	Integrates PGT-A; personalised transfer strategy
STAR (Fairtility) [66]	Fairtility (IL)	CNN + morphokinetics	Ranking with XAI overlay	CHLOE XAI interface; multi-site international use
Ivy (AIVF) [67]	AIVF (IL/US)	Multimodal AI platform	Automated full-cycle analysis	Integrates culture, grading, trigger timing

4. AI-Assisted Prediction of Implantation Potential and Genetic Normalcy

Artificial intelligence (AI) initiated a paradigm shift in assisted reproductive technology by encouraging the prediction of implantation potential and genetic normality of embryos [112, 113]. Over the past several decades, embryologists have relied on visual inspection of morphologic and morpho kinetic features to determine which embryo has potential to implant. It is useful for some as well, but too subjective and evaluative they don't see hidden genetic defectives, as evidenced by the intelligent readers of this post. Nevertheless, these limitations can be surpassed by AI systems that may be trained using large data sets consisting of embryo images and time-lapsed videos as well as clinical information that could facilitate embedding multi-faceted principles of embryo quality into an accurate predictive model.

Focus for the applications of AI in embryo assessment Can broad types of methods simply be categorised as, e.g., machine learning (e.g. CNNs) or deep learning models trained on >1 datasets of embryo features mapped to their labelled implantation results? AI models deliver an embryo-specific implantation likelihood score based on the analysis of small morphologic and morpho kinetic variables including: timing of cleavage, blastocyst expansion rate, inner cell mass quality, fragmentation patterns. These expected values from the model assist embryologists attaching surveillance to embryos and the one with highest probability for success is transferred first. It has been empirically demonstrated that these AI-assisted predictions are of comparable, if not surpassing image classification specificities and sensitivities to the experts' human embryologists while allowing for reproducible and

scalable clinical decision support for in-vitro fertilization (IVF) laboratories.

AI also provides us data on genetic normality, specifically the risk for any chromosomal abnormalities such as aneuploidy. PGT, preimplantation genetic testing [114] still remains the gold standard for diagnosis of chromosomal disorders; however, it is invasive, expensive and does not apply to all cases. These AI models offer an alternative non-invasive method to correlate morpho kinetic patterns to both morphological and genomic truth. Such embryos with distinct cleavage kinetics or abnormal blastocyst expansion could have an increased risk of aneuploidy. It is also possible to predict the likelihood of an embryo being euploid (having a normal number of chromosomes), with high accuracy, without invasive diagnostic tests by modelling large and well annotated data sets association with genetic testing results using AI algorithms enabling more accurate or effective selection of embryos.

Integration of AI-based decisions in the clinical setting would further personalize IVF [115]. Through using the score of implantation probability, along with the prediction genetic normalcy, embryologists are now in a position to use personalized treatment based on specific patient. The use of AI to aid in predicting embryo implantation and genetic health is a major step forward in the assessment of embryos. AI combines morphological, morpho kinetic and clinical data to yield objective, non-invasive and informative assessments that can improve embryo selection and IVF outcomes, shifting reproductive medicine towards a more accurate and tailored approach [116].

Table 6: Integration of Artificial Intelligence in Reproductive Medicine, Genetic Testing, and Gamete Evaluation

Study	Aims of Study	Outcomes of Interest	Dataset	AI Methods	Results
Shoham (2025) [112]	To explore how AI is transforming reproductive medicine and assisted reproductive technologies (ART).	Clinical applications, automation, success rate improvement.	Review of clinical and experimental studies.	Analytical synthesis of AI models.	Demonstrated AI's ability to enhance embryo selection, workflow automation, and personalized treatment.
Doultani et al. (2024) [113]	To assess AI's transformative role in fertility assessment, ART, and reproductive biology research.	Fertility diagnostics, ART optimization, predictive analytics.	Literature-based review.	Comparative assessment of AI approaches.	Identified AI as a catalyst for innovation in fertility prediction and ART success.
Greco et al. (2020) [114]	To review advancements in preimplantation genetic testing (PGT) and its integration with AI.	Genetic screening, embryo selection accuracy.	PGT datasets and clinical outcomes.	Algorithmic and data-driven approaches.	Highlighted the synergy between PGT and AI for improving detection of aneuploidy.
Kakkar et al. (2025) [115]	To present a comprehensive review of AI applications in assisted reproduction.	Efficiency, ethical considerations, clinical integration.	Review of empirical studies and AI systems.	Multimodal AI frameworks.	Concluded that AI is revolutionizing ART through accuracy, transparency, and clinical adaptability.
Zhang et al. (2024) [116]	To discuss emerging AI-based methods in sperm selection for enhanced reproductive success.	Sperm motility, morphology, fertilization potential.	Clinical sperm assessment data.	Deep learning and image analysis models.	AI-assisted sperm selection significantly improved fertilization and implantation outcomes.
Ghaffari & Sohrabei (2025) [117]	To systematically review AI in evaluating sperm and embryo quality during IVF.	Predictive accuracy, embryo and sperm quality metrics.	Aggregated IVF datasets.	Machine and deep learning models.	AI demonstrated high precision in predicting sperm viability and embryo developmental success.

Table 8 Summary of studies demonstrating the surging applications of artificial intelligence (AI) in reproductive medicine for embryo, sperm, and genetic analysis. [112, 113]) analysed the disruptive potential of AI for assessment of fertility and optimization of ART, focusing on automation and personalized decision-making. [114] and [115], that discussed applications of AI with pre-implantation genetic testing and reproductive protocols, covering technological as well as theological aspects. Taken together, these studies demonstrate that AI has the capacity to make a profound impact on clinical efficiency, diagnostic accuracy, and pregnancy success in ART, towards making reproductive health a purely data-driven specialty.

5. SWOT Analysis

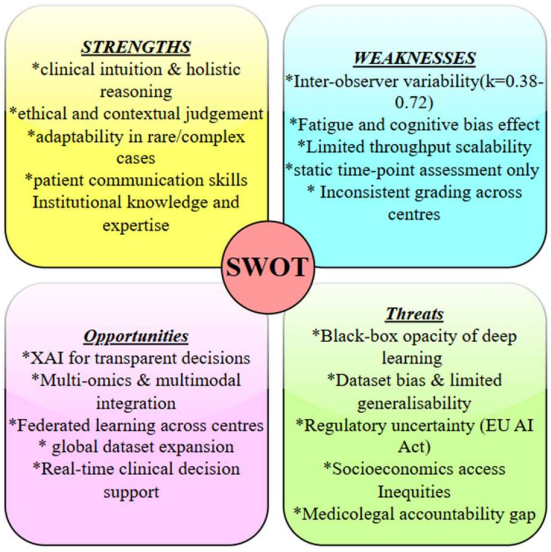

Figure 6: SWOT Analysis- Human vs ML-Based Embryo Assessment.

5.1 Methodology

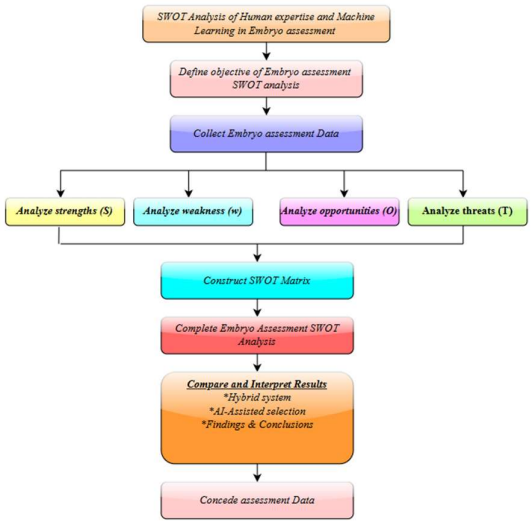

Fig 6: Methodology Flowchart for SWOT-Based Embryo Assessment Study

Methodology Algorithm for SWOT analysis	
Input:	*Let the dataset be represented as D = {H, M}* *where, H = Human expertise-based embryo assessment data, M = Machine learning-based embryo assessment data*
Output:	SWOT = {S, W, O, T}, and comparative evaluation score, C = Comparative performance value
1	Define the evaluation function, f(H, M), where F represents the comparative performance of human expertise and machine learning methods in embryo assessment. ***# Define Study Objective***
2	Collect embryo assessment information, D = {d_1, d_2, d_3, …, d_n}, where di represents embryo assessment observations or clinical data. ***# Data Collection***
3	Define the evaluation parameter set, P = {p1, p2, p3, p4, p5}, where, p1 = Accuracy, p2 = Reliability, p3 = Interpretability, p4 = Scalability, p5 = Clinical Applicability, ***#Parameter Identification***
4	Determine the strength set, S = SH ∪ SM Where SH = Strengths of human expertise, SM = Strengths of machine learning, ***# Strength Analysis***

5	Determine the weakness set, W = WH ∪ WM where WH = Weaknesses of human expertise and WM = Weaknesses of machine learning ***# Weakness Analysis***
6	Define the opportunity set, O = {o1, o2, o3, o4}, this is representing technological and clinical opportunities. ***#Opportunity Analysis***
7	Define the threat set: T = {t1, t2, t3, t4}, this is representing ethical, regulatory, and technical risks. ***# Threat Analysis***
8	Construct SWOT matrix, SWOT = [S W O T] ***#SWOT Matrix Construction***
9	Calculate comparative score, $C = \Sigma (\alpha i\ Pi(H)) - \Sigma (\beta i\ Pi(M))$ where αi and βi are weighting factors, p_i represents performance parameters. ***# Comparative Evaluation***
10	Define hybrid embryo assessment model, $R = \gamma H + (1 - \gamma)M$, where $0 \leq \gamma \leq 1$ ***# Hybrid Model Evaluation***
11	Decision rule: If C > 0 → Human expertise preferred ***# Final Decision*** If C < 0 → Machine learning preferred If C ≈ 0 → Hybrid model preferred

5.2 Strengths

Strengths capture the internal advantages that support positively the performance and adoption of human expertise and ML in embryo assessment.

Strengths	
Human Expertise-Based Assessment	• **Clinical Intuition and Experience**: Developed through, Years of Training, Patient Embryo Work and Watching They are swirled like snowflakes as they work under the microscope, and placed in to finish this crucial step. The human intuition aspect of the response allows both the integration of very subtle visual clues and In addition to clinical information, a calibration to patient specific features was used [120]
	• **Ability to Interpret Complex or Atypical Cases**: the ability to interpret complex cases, atypical cases: human assessor can adapt to rare or atypical cases Ambiguous embryo development patterns: consider variations, making judgements in uncertainty. situations. This may be especially important in special IVF situations where fixed algorithms originally developed may be unsuccessful.
Machine Learning-Based Assessment	• **Consistency and Reproducibility**: ML systems can deliver normalized assessments which are consistent and reproducible. To eradicate the inter- and intra-observer variation in human assessment [122].
	• **Rapid Processing of Large Datasets**: ML can analyse the several thousands of embryo images and draw informative conclusions in a short period of time. The time is much shorter than that needed by human embryologists, and is thus applicable to the clinical IVF clinics have contexts that follow a trend of high-throughput.
	• **Objectivity and Data-Driven Insights**: straight from big annotated training data and provide measurable predictions which are independent of the way one interprets a work, which can be biased or personal.

Table 7: Strengths of Human vs. ML-Based Embryo Assessment

Aspect	**Human Expertise**	**Machine Learning (ML)**
Clinical Judgment	High—developed through training and real-world experience	None—inferential only from data
Case Adaptability	Strong—capable of adjusting to complex, atypical scenarios	Limited—dependent on training data diversity
Consistency	Variable—subject to fatigue and observer variability	High—same input yields same output every time
Speed of Evaluation	Moderate—manual, time-consuming	Very fast—can evaluate thousands of embryos in minutes
Bias-Free Analysis	May be influenced by subconscious bias or emotion	High objectivity—data-driven evaluation
Scalability	Limited by human resources and time	Easily scalable across clinics once trained

5.3 Weaknesses

Weakness: What are the potential faults/difficulties a system might encounter that would make it inefficient or unreliable? When used for embryo selection in IVF, they both face notable drawbacks as well: human expertise-based assessment and machine learning based assessment.

Weaknesses	
Human Expertise-Based Assessment – Weaknesses	• **Subjectivity and Inter-Observer Variability:** There will always be a difference of opinions from one embryologist's evaluation to another. Despite standardized rule-based grading systems, discretion and interpretation differ enormously between individuals [124].
	• **Scalability Limitation**: Human-based embryo analysis is a very labour-intensive process, and it does not scale to high patient throughputs without personnel or time expansion; thus, limiting practical use in the high-throughput IVF clinic [125].
Machine Learning-Based Assessment – Weaknesses	• **Dependence on Quality and Volume of Training Data**: ML models require large, annotated datasets with reliable outcome labels (e.g., implantation success). Poor or biased datasets can lead to inaccurate or non-generalizable predictions [126].
	• **Lack of Interpretability (Black-Box Models):** A large number of ML algorithms such as deep learning models in particular, are black boxes. This have little or no insight on how the decisions are being made. This lack of interpretability can have detrimental effect on clinical trust and system uptake [127].

Table 7: Weaknesses of Human vs. ML-Based Embryo Assessment

Aspect	**Human Expertise**	**Machine Learning (ML)**
Evaluation Consistency	Low—subject to personal interpretation and fatigue	High consistency, but relies heavily on training quality
Scalability	Limited—requires more staff for higher workload	High—can scale easily once deployed
Data Dependence	Relies on experience, not large data volumes	Requires large, well-labelled datasets for training
Decision Transparency	High—embryologists can explain their reasoning	Low—decisions often not interpretable without explainable AI
Adaptability	Flexible but subjective	Rigid if not trained on diverse or edge-case scenarios
Bias Risk	Human bias and variability	Risk of algorithmic bias if training data is unbalanced

5.4 Opportunities

Opportunities in our SWOT analysis refer to "external conditions that will help us achieve the minimum standard to which assessment system should be developed", such as new developments or trends outside of machine learning (ML) technologies that could enhance strengths and/or alleviating weaknesses in embryo assessment [128], unlike threats. Such opportunities suggest innovation, implementation and–hopefully–clinical impact.

Opportunities	
Key Opportunities for Embryo Assessment Advancement	Incorporation of ML in Clinical Decision Support Systems (CDSS) With IVF, it will help but not replace physicians One such system (a clinical decision support system or CDSS, in medical parlance) [129], could provide guidance on ranking of embryos, predict which may be best able to successfully implant and give unbiased criteria for viability beyond what human researchers otherwise indicate. Therefore, the system of CDSS will reduce human errors, standardize selection, and help to improve the clinical efficiency. IVF platforms incorporating ML scoring tools within real-time embryologist dashboards [130].
Hybrid Human-AI Models for Improved Accuracy	A hybrid approach using the intuition of embryologists together with AI is in many instances likely to work better than either method alone. Such systems offer mechanisms to allow clinicians to Mold or corroborate AI predictions based on their own experiences; this in turn can lead to even greater trust and predictability. It has been demonstrated that hybrid system enhances implantation prediction over single-ended evaluations [131].

Development of Standardized Embryo Assessment Protocols	The spread of machine learning tools that can facilitate development of such consistent global criteria and the for on slow-motion image [132]. The more standardized be input protocols, the Bett model performance and more compatible are models from different hospitals in different countries. Opportunity Example: Universal agreement on embryo viability standard with AI based thresholds.
Development of Standardized Embryo Assessment Protocols	The spread of machine learning tools that can facilitate development of such consistent global criteria and the for on slow-motion image [132]. The more standardized be input protocols, the Bett model performance and more compatible are models from different hospitals in different countries. Opportunity Example: Universal agreement on embryo viability standard with AI based thresholds.
Advancements in Explainable AI (XAI)	Explainable artificial intelligence (XAI) has thus far been created mainly for addressing those out-of-this-world challenges [133]. With recent progress in deep learning models where they can provide easy-to-understand humans have better chance to be capable to acknowledge the language and data manipulated by of the software testers [134] for whom debug programs are normally paper only graphic Artists, stop glitch off saving grain before being let down into bed reproduce.

Table 9: Opportunities in Human-AI Embryo Assessment

Opportunity	Human Expertise	Machine Learning (ML)	Collaborative Potential
Integration into CDSS	May benefit from AI-assisted suggestions	Can be integrated into digital clinical workflows	Yes → improves decision support
Hybrid Human-AI Models	Adds clinical nuance and flexibility	Adds scalability and objectivity	Yes -> enhances prediction accuracy
Standardization of Protocols	Currently variable across labs	Encourages unified data formats and metrics	Yes –> enables global benchmarking
Explainable AI (XAI) Tools	Already explainable via human logic	Becoming interpretable through visual tools	Yes -> improves interpretability and trust

5.5 Threats

SWOT framework threats are outside issues or risks that may have an impact on the efficiency, acceptability, or ethical application of embryo assessment tools [135]. The risks are posed to both conventional human expertise and machine learning (ML)–based systems, which now carry the additional assure of effectiveness with AI being integrated into clinical decisions for assisted reproductive technologies (ART) [136].

Key Threats in Embryo Assessment Using Human Expertise and Machine Learning	
Resistance to Adoption by Clinicians	To leave these systems in the hands of AI to determine the outcome of important emotional, ethical, biological decisions is something that many embryologists and reproductive specialists [137] are wary about. ML systems have come under much speculation as to being "black boxes," not accounting for clinical context or missing new cases. For instance, AI system-assisted embryo selection technology could have high accuracy (performance), but the black box that is deep learning is fostering a current. This does not sit well with anyone who cannot comprehend it [138].
Ethical and Legal Concerns	Thus, it's not surprising at all that AI in the area of reproductive decision-making raises very serious ethical issues. We can classify these into the following three categories: bad consequences liability, bias-free algorithmic prediction, and AI-based consent tools. There are also some issues about what non-human systems choose to do. Violate the patient's rights, and moral obligations As mentioned in [139], AI can be used to: Equity, transparency and justice are the elements that health needs.
Potential Overreliance on AI at the Cost of Clinical Judgment	t will be as if expert judgment was trivialised and that it's been added in that we have now fate less articulate a blow to expert opinion. Overreliance on ML output may lead to missing out on potentially important clinical context like may relate to uterine health, hormone level or ART history [140].

5.5.1 Data Privacy and Security Concerns

In order to train up AI models and ensure that their level of learning is always up to date, gargantuan data sets are needed as well. Amid such a massive influx of Introduction of this huge amount of information from patients´ or embryo genomes will induce great risks to the privacy when collected, stored and used [141]. The data are sensitive; it is easy to misuse and leak that data and the harms introduced could result in a collapse of trust both in AI the processes that run the machinery (that is, algorithmic bias) and IVF clinics [142].

Table 10: Threats in Human vs. ML-Based Embryo Assessment

Threat	Human Expertise	Machine Learning (ML)
Clinician Resistance to Change	Low traditional method trusted	High skepticism due to algorithm opacity
Ethical and Legal Risks	Minimal regulated by established practice	High ethical ambiguity in automated embryo ranking
Overreliance and Skill Devaluation	Not applicable	Possible risk of deskilling and blind trust
Data Privacy and Security Concerns	Lower less data sharing involved	High requires massive datasets and cloud systems
Bias and Algorithmic Discrimination	Bias is personal and varied	Systematic bias possible if data is unbalanced
Litigation Risk	Low—professional discretion often protected	High—legal responsibility for AI-driven decisions

However, while the new vistas that machine learning fertility technology has buoyed hope for in embryo screening sound so great, they are to be deployed at all they must similarly show respect for and stick to strict laws about one thing: human agency. Failure To overcome such risks will have an impact on the IVF outcome, and will compromise the integrity of confidence in IVF technologies [144].

6. COMPARATIVE ANALYSIS

Machine learning fertility technology promises the new frontiers of embryo screening, but they will require proof as per their looks. Against them there are exacting laws which, with the help of another extremely sensitive feature, ensure that they always remain on the straight and narrow path. They are precisely mediated and directed by strict rules already assisted with another very sensitive feature, which makes them stay in the straight and narrow path human. oversight. Otherwise, patient outcomes will be affected and the trust of IVF technologies in the society will be lost.

6.1 Performance Metrics

When assessing embryo assessment methods, the following performance parameters should be looked at:

Table 11: Evaluating embryo assessment methods

Metric	Human Expertise	Machine Learning
Accuracy	Moderate (typically 60–75%) – depends on experience and method [74]	High (>80% in many models like CNNs – Khosravi et al., 2019) [75]
Sensitivity	Variable – may miss subtle indicators of embryo non-viability	High – captures complex visual and developmental cues
Specificity	May over-select borderline embryos (false positives)	Balanced – especially with balanced training datasets
Reproducibility	Low to Moderate – inter-observer variability is common	High – consistent outputs for same inputs
Scalability	Low – time and labour-intensive	High – scalable with minimal cost once trained
Processing Time	Moderate to High – manual evaluation takes minutes per embryo	Very Low – milliseconds per embryo in batch mode

Human evaluation falls short in terms of accuracy, Reproducibility, Speeds is better than ML system, whereas accuracy, Reproducibility and Speed are better than Human Evaluation, Interpretability is better in Human Evaluation where available. In large-size IVF centres [76]

6.2 Cost-Benefit Analysis

Table 11 A comparative cost analysis of both investment costs and operational impacts into account.

Factor	Human Expertise	Machine Learning
Initial Cost	Lower – standard staff salaries, microscopes	High – infrastructure, ML software licenses, cloud storage
Training & Skill Upkeep	Ongoing – training embryologists, certification	One-time model training + periodic re-training
Operational Cost	High – requires multiple staff, time-intensive	Low – automation reduces marginal cost per embryo
Throughput Potential	Low to moderate – depends on staff-to-patient ratio	High – thousands of evaluations possible per day
ROI (Return on Investment)	Long-term – based on experience and clinical reputation	Long-term – scalable solutions save time and improve outcomes
Cost of Errors	High – misjudged embryos lead to failed cycles or miscarriages	Potentially lower – if trained on high-quality, unbiased data

While the initial costs of a model-based approach are high, model-based systems are more efficient and scalable, particularly when treating a large volume of patients. Hybrid systems can help the balance the initial expense and performance.

6.3 Acceptance and Usability in Clinical Settings

Adoption of any form of assessment within IVF clinics is subject to the clinical acceptance, feasibility of regulation and simplicity of the method. Integration with legacy processes.

Table 12 Comparative Analysis of Human Expertise and Machine Learning in Assisted Reproductive Technologies (ART)

Category	Human Expertise	Machine Learning
Clinical Acceptance	Very High – trusted for decades	Moderate – growing but cautious due to black-box limitations
Learning Curve	Requires years of hands-on training	Moderate – requires basic tech literacy for AI-assisted platforms
User Control	Full – decisions fully under clinician's control	Partial – requires trust in algorithmic recommendations
Integration with Lab Systems	Fully compatible	Needs software/hardware adaptation; increasing vendor support
Trust from Patients	High – patients prefer clinician-led decision-making	Mixed – depends on explanation and counseling
Regulatory Approvals	Standardized globally (e.g., ESHRE, ASRM)	Under review in most countries; GDPR and HIPAA-sensitive

Traditional approaches are comfortable for clinicians, but inviting apps and explainable AI (XAI) tools, as well as transparent outputs of AI can enhance usability and trust.

7. Artificial Intelligence Age – Human Expertise vs. Machine Learning – A full-fledged Level Comparative Analysis.

7.1 Accuracy and Reliability Comparison: Currently, morphological and morpho kinetic parameters [145]. Working embryologists are usually able to correctly select embryos with good developmental potential [146]. Nonetheless, this technique is still subjective since it relies on human discretion. Variations in training, experience, and interpretation can result in inter laboratory and observer variability. Unlike with ML and AI, this results in less standardized and repeatable evaluations [147]. Some advanced AI methods can analyse large datasets of embryo images and time-lapse videos. Likewise, deep learning algorithms like Convolutional Neural Networks (CNNs) can identify minute and concealed features that cannot be seen by the naked eye [148]. Forecasting the outcome has been greatly improved by employing AI in embryo evaluation setting, and recent research has suggested that it accurately assesses the viability of embryos better than human specialists whilst minimizing inter- and intra-observer variation [149]. As a result, ML has proven to be a productive and reliable aid for embryo development prediction and selection in large scale of IVF applications [150].

7.2 Decision-Making Transparency: Decision explainability is one of the main differences between machine learning and human experts. Human experts can explain their decisions in a clear and understandable way based on visible and measurable embryo characteristics, which can then be shared with clinicians and patients [151]. In contrast, most Artificial Intelligence (AI) models work like “black boxes.” They give predictions, but they do not clearly show how or why those predictions were made. This transparency challenge exists in clinical practice because although AI might have a very high

predictive value [152] it is not transparent. In medical settings, it is important for ethical and regulatory reasons to understand why certain embryos are selected [153]. Therefore, many studies on embryo assessment are now focusing on model interpretability. These studies try to develop methods that can explain how AI systems make their decisions and provide more insight into the embryo assessment process [154].

7.3 Clinical Adaptability and Patient Outcomes: The human capacity is so flexible that the embryologists can take many patient specific factors in their choice of embryo selection such as age, ovarian reserve, hormonal levels and previous IVF history [155]. This notion of knowledge context might be a daunting task to duplicate in AI models as it was expected we could further piggyback with the integration of clinical information and image-based evaluations for personalized risk estimation [156]. Thus AI when well implemented will serve as adjunctive tool increasing the ability to generalize in clinical settings rather than replace human mind. In low sample numbers, initial data has revealed that human grading supplemented by AI-assisted assessment is able to diagnose one candidate with a greater propensity to develop into a viable blastocyst [157], which resulted in increased implantation at time of transfer and elevated live birth rates as well as significantly reduced transfers of embryos considered poor for developmental potential [158]. It renders new reproductive care more personalized (individual-based), so much that what an intuition (person) sees, tastes and feels or computational based prediction [159] is less impactful about the patient.

7.4 Case Studies and Reported Success Rates: There are numerous studies reporting the clinical application of AI assisted embryo evaluation. with positive results. CNN (Convolutional Neural Network) models have been found effective in predicting the implantation and an achievement rate of 80% – 86%, achievement of high accuracy (over 85–90%) compared to the performance of expert embryologists who typically have an accuracy of around 75%. 70–80%. Individuals have employed deep learning along with time-lapsed imaging to boost embryo ranking and aid in embryo selection. higher implantation potential. It has also been found to better agree with genetic normality. Commercial AI platforms such as Embryoscope, Life Whisperer and ERICA have now reported equal or superior performance compared to ‘old fashion' embryo assessment. methods [160]. In some clinics, too, users reported higher rates of pregnancy and live birth after doctors employed AI. Make recommendations and assist with clinical decision-making [161]. These examples illustrate how AI can enhance standardization and efficiency in business operations. Improve subjectivity in embryo assessment with human expertise. Overall, both human knowledge and machine All learning benefits and drawbacks, and learning has its benefits and drawbacks. Whether it is a matter of judgment or objectivity, AI is proving to be more objective than Embryologists do, which offer careful and context-based judgment. Analyses that are consistent and data driven. Hence, a human touch and the assistance of AI will work best together; Optimize Embryo Selection, transparency, flexibility and patient care.

Table 13: A table showing comparing human expertise and machine learning in relation to Embryo Assessment:

Aspect	Human Expertise	Machine Learning (AI/ML)
Accuracy and Reliability	Highly dependent on training and experience; subject to inter- and intra-observer variability; may miss subtle patterns	Standardized and reproducible; can detect subtle morphological and morphokinetic patterns; often matches or surpasses human accuracy
Decision-Making Transparency	Transparent and explainable; reasoning based on observable embryo characteristics	Often a “black box”; outputs may be accurate but not easily interpretable; explainable AI (XAI) needed for rationale
Clinical Adaptability	High; can incorporate patient-specific factors (age, ovarian reserve, previous cycles)	Moderate; can integrate clinical data but may lack nuanced contextual understanding; best used as a complementary tool
Patient Outcomes	Dependent on skill and consistency; variability can affect implantation and live birth rates	Can improve outcomes when integrated with human judgment; better embryo ranking and selection; reduces transfer of low-potential embryos
Data Requirements	Low; relies on visual observation and manual grading	High; requires large datasets of images, time-lapse videos, and clinical/omics data for training
Speed and Scalability	Limited; time-consuming and labour-intensive, especially in high-volume clinics	High; rapid evaluation of large numbers of embryos; scalable across multiple laboratories
Limitations	Subjective; variable between embryologists; may miss hidden developmental issues	“Black box” nature; dependent on data quality; requires validation and integration; lacks full clinical intuition
Reported Success Rates	Generally, 70–80% accuracy in implantation prediction	Often 85–90% accuracy; demonstrated improved implantation and live birth rates in AI-assisted clinics

8. Explainable AI to Embryo Assessment: Transparent XAI Processes transforming IVF Success

The success of any collaborative framework is based on the XAI tools. Table 6 provides a summary of the major XAI methods The mechanisms, output types and specific clinical applications of these that can be utilized in embryo evaluation.

Table 14: The below table provides a compilation of techniques and knowledge concerning Explanatory AI (XAI) for embryo assessment, meaning, outputs and applications in clinic scenarios.

XAI Technique	Mechanism	Output Type	Embryology Application
Grad-CAM [68]	Gradient-weighted Class Activation Mapping	Visual heatmap over embryo image highlighting predictive regions	ICM morphology, TE continuity highlighted; identifies novel perivitelline features
SHAP [69]	SHapley Additive exPlanations	Quantifies marginal contribution of each input feature to prediction	Reveals time-lapse frame importance; morphokinetic parameter weighting
LIME [70]	Local Interpretable Model-agnostic Explanations	Approximates model locally with interpretable surrogate	Feature-level explanation for individual embryo predictions
Attention Maps [71]	Transformer/LSTM attention weights	Temporal attention over time-lapse sequence frames	Identifies which developmental time windows drive quality prediction
Counterfactual XAI [72]	Minimal change to alter model decision	'What-if' clinical narrative for embryologist review	'If compaction occurred 4h earlier, ranking would increase by 2 positions'
Concept Activation Vectors [73]	TCAV – tests concept importance	Tests whether human-defined concepts influence predictions	Validates biological consistency of model (e.g., fragmentation concept)

9. LEGAL, ETHICAL AND SOCIAL CONSIDERATIONS

9.1 Consent and Use of Patient Reproductive Data: Screening for some of these conditions using AI and ML poses ethical [132] and legal questions related to consent as well as data privacy [162]. Embryo images [162], time-lapse video [164] and omics data are intimate [163] as well as inherently sensitive; they contain information that can pertain not only to reproduction health, but genetic susceptibilities. These data can flow out to more healthcare systems for sharing with patient permission; to be garnered for collection, storage and use for generation of AI algorithms in training, validation and clinical decision support. And transparency around how it is being applied, who has access to it and for what duration will be key in maintaining confidence.

9.2 Regulation of AI-Based Medical Devices in Reproductive Health: Although this involves risk beyond embryological tests, its competition the AI devices embryo evaluation are more like a medical device and must comply with standards FDA equivalent safety and efficacy [164] To our best knowledge only authorities responsible for the approval of FDA or EMA products [165] as well as other national institutions issued recommendations regarding AI technologies in reproductive domains. The rules are typically that the results must be validated deeply, followed by strict monitoring and reporting of the results to ensure, where it can, that no harm is caused to a patient [166]. In addition, the details of an AI (such as the way in which information is being updated), also play a part. Future operation of our regulatory systems should consider (retraining) taking account so that there are gaps in enforcement. if it is desired, that there is no formal assurance that it avoids (at least unwanted) cognitive biases or mispredictions [159]. such types of an enslavement phenomenon need to be prevented. But these regulations are crucial to allow AI technology to be It has been safely used in IVF clinics and it requires trust in the algorithm and from the patient to the clinician, which they have to demonstrate in the case of IVF algorithms[167].

9.3 Ethical and legal issues related to the evaluation of the embryo using AI technologies:

From the ethical point of view, it is already controversial that algorithm-based embryo selection is: algorithm-driven embryo selection AI sorts embryos by the terms of “estimated implantation” or “genetic normality” [168]. Algorithmic mechanistic automations may increase the likelihood of pregnancy yet devolve into debates over issues of agency, bias and misuse that have never before been relevant in reproduction or would repeat problems already present in reproductive therapies cannabinoids 169. Moreover, there are ethical issues in terms of how much impersonal “value” price tags have been placed on embryos and decisions made with predictions on what prospects should be adopted or frozen or disposed of [171]. Reliance on AI for clinical decision-making likewise removes the moral reasoning and empathy from this process — anathema to patient-centred care.

It is the moral way to go according to natural law theory that AI egg selection should be an aid, not a substitute for human wisdom. Embryologists and clinicians should critically interpret inferencing or AI using an amalgamation of algorithmic results and patient values

[172], clinical context and informed consent. It is also imperative to disseminate performance bounds and uncertainties transparently in order to prevent overconfident use of the algorithmic output. The social wise should take into account whether AI applied in reproductive health will be well received by the society and how it would be sensitive to cultural/Clinical wisdom (i.e., all patients may not have equal privileges of enjoying benefiting AI processing than another group of patients, or a healthcare delivery setup) [173].

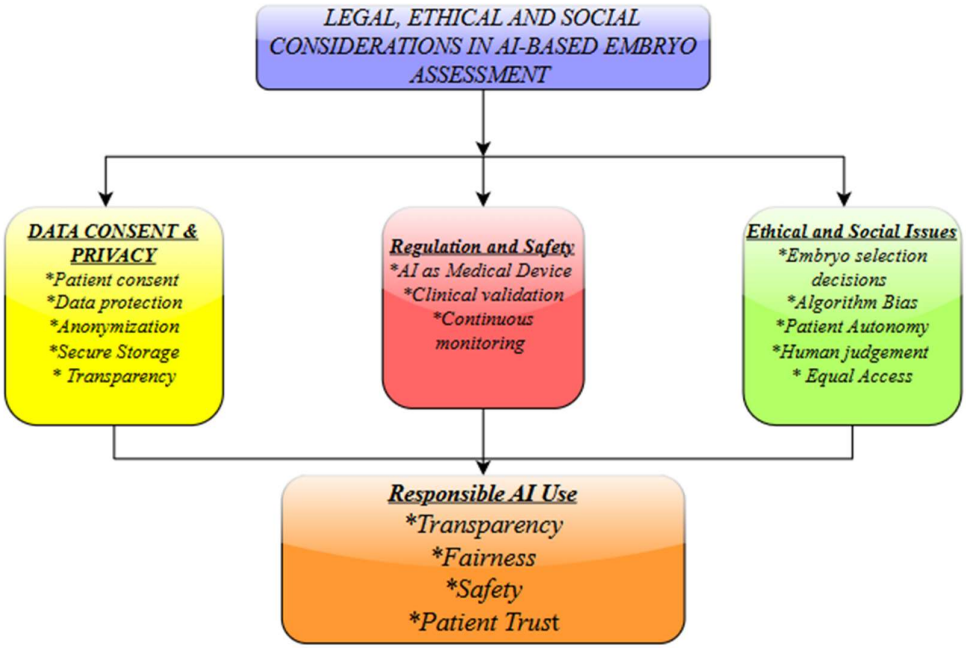

Fig 8: Legal, ethical and social considerations in AI- Based Embryo assessment

The ELSS considerations on the use of AI in embryo assessment highlight the importance of informed consent, regulation, transparency, and responsible use in this context. The balancing of technological innovation and patient autonomy, safety and fairness are a fundamental part of utilizing AI to be used responsibly, with trust and in an ethical role for reproductive medicine.

Table 15 Human Expertise, AI/ML, and Ethical/Regulatory Considerations for a comprehensive overview of embryo assessment in ART

Aspect	Human Expertise	AI/ML-Based Assessment	Ethical/Regulatory Considerations
Accuracy and Reliability	Dependent on experience and training; subject to inter- and intra-observer variability; may miss subtle patterns	Standardized and reproducible; can detect subtle morphological and morphokinetic features; often surpasses human accuracy	Must ensure AI predictions are validated clinically to maintain accuracy and reliability
Decision-Making Transparency	Fully interpretable; reasoning based on visible embryo features	Often "black box"; decisions may lack intuitive explanation; explainable AI (XAI) improves interpretability	Transparency is required for ethical use; patients and clinicians must understand AI outputs
Clinical Adaptability	Highly adaptable; incorporates patient-specific factors, previous IVF history, and contextual judgment	Moderate adaptability; can integrate clinical and omics data but may lack nuanced contextual insight; best used alongside human expertise	AI deployment must align with clinical protocols; human oversight ensures patient-centered care
Patient Outcomes	Dependent on skill, experience, and consistency; variability affects implantation and live birth rates	Can improve outcomes when integrated with human judgment; improves embryo ranking and selection; reduces transfer of low-potential embryos	Ethical use requires optimizing outcomes without bias; fair access to AI-assisted ART is essential
Data	Minimal; relies on visual	High; requires large datasets of	Collection of sensitive

Requirements	inspection and manual grading	images, time-lapse videos, clinical data, and omics profiles	reproductive data requires informed consent, secure storage, and anonymization
Speed and Scalability	Limited; labor-intensive; difficult to scale in high-volume clinics	High; rapid and scalable evaluation of large numbers of embryos	AI systems must meet regulatory standards for safe and consistent use at scale
Bias and Variability	Subjective; inter-observer and intra-observer variability can affect embryo selection	Reduces human bias but can reflect biases in training datasets; model generalization is critical	Regulatory oversight needed to prevent bias and ensure equitable care; continuous monitoring and validation required
Ethical Implications	Decisions influenced by clinical judgment and patient discussions; inherently human-centered	Algorithm-driven decisions can raise concerns about embryo valuation, autonomy, and bias; should remain complementary	Ethical frameworks required for consent, transparency, fairness, and accountability in AI-assisted embryo selection
Regulation and Compliance	Guided by professional standards, accreditation, and best-practice protocols	Subject to medical device regulations (FDA, EMA, national bodies); requires validation, monitoring, and updates	Ensures safe and ethical deployment; compliance with data protection and patient safety standards
Reported Success Rates	Typically, 70–80% accuracy in implantation prediction	Often 85–90% accuracy in predicting implantation potential and genetic normalcy; improves clinical outcomes when integrated with human expertise	Continuous monitoring and reporting ensure reliability and ethical practice

9. CONCLUSIONS AND FUTURE PROSPECTS

9.1 Summary of SWOT Insights: Human expectation versus machine learning (ML) in embryology. View it from this angle, the moral connoisseur and ethical watchdog is impossible to replace with just an automation. And in the context of such a complex clinical scenario, and patient's characteristics experienced embryologist may 'deduct' and 'substract' interfering to take part into decision-making process. But the conventional manual analysis which is subjective, and depends on both inter- and intra- operator variation has drawbacks such as being time consuming. AI/ML algorithms provide with high accuracy and reproducibility as well the aptitude to capture morphological/morpho kinetic minute characteristics which may be not so easily visible to naked human eye. They provide a scalable and objective approach for people to analyse large datasets, which may lead to better selection of the embryos and conceivably better clinical outcomes. But AI has limitations, from its own black-boxed decision-making to its requirements for good quality data, and the need for robust testing. Ethical and regulatory aspects, such as patient consent, issues of data privacy or fairness in supply are the fundamental prerequisites to address when deploying AI-supported technology in a responsible manner.

9.2 The future of AI collaboration with embryo evaluation: Human expertise is irreplaceable when it comes to embryo evaluation. than ai. Rather, AI will help embryologists. It is also useful for doctors and the embryologist for better and consistent decisions. And best of all, AI can automate some of the tasks and save time as well as make less repetitive and more precise work. A More advanced AI features such as deep learning or computer vision, which can efficiently analyse time-lapse imagery, are being employed in cases like this. To assign quality grades to embryos and to remove embryos while they are in their egg. The scores might influence embryologists to choose the embryos that are most likely to survive. flourish. But the ultimate decision should also rely on the doctor's judgment as well as other clinical factors such as the patient's The general health of the patient and ethics. The ladybird moth larvae are hybrid and as a result the selection of embryos becomes more precise. and that is customized to a person's profile.

9.3 Required need for Standardized Datasets, Gaps in the International Regulatory frameworks: AI will function only if it is given high-quality data, and if there are international regulatory frameworks. A lack of standardized datasets and frameworks of international regulation will make it difficult to implement AI. The processes, labs and lab products involved in imaging today vary significantly between facilities which create challenges for deploying a one size fits all AI model. As such, excellent quality, internationally viable datasets are in high demand1. It should be based on standardized data collection, image processing and annotation procedures in centres. For its own safety and ethics, policy will also need to develop global standards to help guide the safe use of A.I. in reproductive medicine so that patients aren't

unduly put at risk by the technology. Such guidelines would describe clinical testing, the monitoring of the tools over time, provisions for data privacy and updating newer versions of software, and guaranteed equitable access to technologies by all patients.

9.4 Vision of Fully Integrated AI Systems in Next-Generation IVF Clinics: Ultimately this leads the AI into IVF for a completely automated data-driven individual embryo assessment. Future clinics ` space would be bi directional co- establishment of high stratification imaging that can be matched with effect of time-lapse with direct observation, omics bench mark and Ai predictions on generations as scaffolding. Software operating within them could continuously assess embryos' quality, anticipating which are poised to implant and signalling genetic abnormalities that embryologists and physicians might be able to weigh against some ethical as well as patient context. A technology-human combo like that could change the success rates of IVF, cut down on waste and spare patients emotional and financial trauma, they said. And in the end, it is all about the vision precision reproductive medicine coming to fruition: An AI-human powered new dawn of sorts aiming to offer a founding role with embryo selection that's targeted towards the patient with consistency and reliability bridging forward personalisation on one side and ethical integrity on the other.

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