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Artificial intelligence (AI) approaches to male infertility in IVF: a mapping review

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Abstract

Background Male infertility contributes to 20–30% of infertility cases, yet traditional diagnostic and treatment methods face limitations in accuracy and consistency. Artificial intelligence (AI) promises to transform male infertility management within in vitro fertilization (IVF) by enhancing precision and efficiency.

Objective This study aims to map current AI applications in male infertility, evaluate their performance in IVF contexts, identify gaps in research, and propose strategies for clinical adoption.

Methods We conducted a mapping review of 14 studies, sourced from PubMed, Scopus, IEEE, and Web of Science up to 2024. Using PRISMA guidelines, we systematically searched titles and abstracts with keywords like "IVF," "AI," and "sperm analysis." Two authors independently screened records, extracted data on AI techniques, sample sizes, and outcomes, and categorized applications through content analysis, resolving discrepancies via consensus.

Results AI employs tools like support vector machines (SVM), multi-layer perceptrons (MLP), and deep neural networks across six key areas. These include sperm morphology (e.g., SVM with AUC 88.59% on 1400 sperm), motility (e.g., SVM with 89.9% accuracy on 2817 sperm), and non-obstructive azoospermia (NOA) sperm retrieval (e.g., gradient boosting trees [GBT] with AUC 0.807 and 91% sensitivity on 119 patients). AI also predicts IVF success (e.g., random forests with AUC 84.23% on 486 patients) and assesses sperm DNA fragmentation. Research surged since 2021, with 8 of 14 studies (57%) published between 2021 and 2023, reflecting growing interest..

Conclusions AI enhances diagnostic accuracy and treatment outcomes in male infertility. Future steps include multicenter validation trials, AI-driven sperm selection for IVF/ICSI, and standardized methods to ensure clinical reliability. Addressing ethical concerns like data privacy will further enable AI to improve IVF success globally.

Keywords Artificial intelligence (AI), Male infertility, IVF, Systematic review

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Introduction

Infertility affects many couples. Male factors cause 20–30% of cases [1]. Key causes include biological, physiological, lifestyle, environmental, and socio-demographic factors [2], with around 70% of cases remaining unexplained [1]. Non-obstructive azoospermia (NOA) is the most severe form. It impacts 1% of men and 10–15% of infertile men [3]. Male infertility rates are highest in Africa and Eastern Europe, impacting an estimated 30 million men globally [4]. Current management strategies include hormonal therapies, which often have limited efficacy due to variable patient responses [5], and surgical sperm retrieval, which carries risks such as testicular damage and inconsistent success rates due to difficulties in predicting viable sperm presence [6, 7]. Assisted reproductive technologies (ART) such as intrauterine insemination (IUI), in vitro fertilization (IVF), and intracytoplasmic sperm injection (ICSI) are widely used to enable fertilization in cases of low sperm quality or count, but these approaches often fail to address underlying causes and can pose risks to both mother and fetus [8].

Despite these advancements, male infertility management faces significant limitations that hinder its effectiveness. Traditional semen analysis, a cornerstone of diagnosis, relies heavily on manual assessment, leading to inter-observer variability, subjectivity, and poor reproducibility [9]. This subjectivity complicates the accurate evaluation of sperm parameters such as morphology, motility, and concentration, which are critical for treatment planning [10, 11]. Furthermore, conventional diagnostic tools often lack the precision to detect subtle or multifactorial causes of infertility, such as sperm DNA fragmentation (SDF) or early-stage testicular dysfunction, limiting their ability to guide personalized interventions [12, 13]. Predictive models based on traditional statistical methods also struggle to integrate the complex interplay of clinical, environmental, and lifestyle factors, resulting in suboptimal accuracy for forecasting IVF outcomes or treatment success [14, 15]. These gaps contribute to delayed diagnoses, inappropriate treatment selections, and reduced success rates in ART procedures.

Artificial Intelligence (AI) is poised to revolutionize the diagnosis and treatment of male infertility by addressing these specific limitations. AI algorithms can enhance diagnostic accuracy by automating sperm evaluation, reducing variability, and identifying abnormal sperm characteristics with greater consistency than manual methods [16]. For instance, machine learning models can analyze sperm morphology, motility, and DNA integrity with high precision, overcoming the subjectivity inherent in traditional assessments. AI-driven predictive tools also offer the potential to integrate diverse data types—such as clinical parameters, imaging, and patient history—to improve the prediction of sperm retrieval success, fertilization potential, and IVF outcomes. In key areas like NOA management, AI can assist in identifying viable sperm in testicular biopsies, a task that remains challenging with current histopathological techniques. Additionally, AI-powered approaches can optimize treatment selection by pinpointing patients likely to benefit from interventions like varicocele repair or hormonal therapy, thus avoiding unnecessary procedures.

While AI holds significant promise for enhancing accuracy, efficiency, and accessibility in healthcare, many applications remain in early development and require further validation for widespread clinical use [17]. This mapping review examines the current applications of AI in addressing male infertility within the context of IVF, focusing on its role in overcoming the limitations of traditional management. By categorizing AI applications in sperm analysis, diagnostic tools, treatment selection, and outcome prediction, this study identifies promising advancements, highlights critical research gaps, and suggests future directions for integrating AI into clinical practice. Through this comprehensive overview, we aim to advance the field by underscoring how AI can bridge existing shortcomings and improve outcomes for couples undergoing IVF.

Methods

Study design

This systematic mapping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. In 2024, we conducted a systematic search and a scoping review to identify the outcomes of using AI in addressing male infertility issues within the context of IVF. This review was based on the Joanna Briggs Institute (JBI) method for scoping reviews [18] and adhered to the PRISMA extension for scoping reviews (PRISMA-ScR) checklist [19].

Information sources

We conducted a comprehensive literature search across the electronic databases PubMed, Scopus, IEEE, and Web of Science. These databases were selected to ensure broad coverage of relevant disciplines: PubMed for its extensive biomedical and reproductive medicine literature, Scopus for its interdisciplinary scope including health sciences and technology, IEEE for its focus on engineering and AI-related advancements, and Web of Science for its high-quality, peer-reviewed publications across multiple fields. This combination aligns with our research objective of mapping AI applications in male infertility within the IVF context, which requires integrating medical, reproductive, and technological perspectives. The search focused on titles and abstracts of studies published up to 2024. We also manually reviewed reference lists of included studies and relevant reviews to identify additional studies, ensuring a thorough capture of pertinent literature.

Search strategy

Our search for relevant papers followed a systematic process, starting with the identification of keywords, formulation of a search strategy, and selection of appropriate data sources. The search terms were designed to align with our primary research question: "What are the current applications of AI in addressing male infertility within the context of IVF, including diagnosis, treatment optimization, and outcome prediction?" Initially, we selected keywords based on this question, focusing on two core concepts: "In Vitro Fertilization" (e.g., IVF, assisted reproductive technology, ICSI) and "Artificial Intelligence" (e.g., machine learning, neural networks, deep learning). To ensure comprehensive coverage, we incorporated male infertility-specific terms (e.g., sperm analysis, azoospermia, varicocele, DNA fragmentation) identified as relevant through a preliminary scoping of the literature. These terms were refined through iterative testing to maximize relevance and effectiveness, as detailed in Supplementary File 1.

The final search strategy grouped synonyms into two distinct sets: Set 1 included "In Vitro Fertilization" and its synonyms, while Set 2 encompassed "Artificial Intelligence" and its related terms, supplemented by male infertility descriptors. The structure [(Set 1) AND (Set 2)] was applied using Boolean operators (AND, OR) to combine terms effectively and optimize results. This approach ensured that the search captured studies addressing AI's role in male infertility management within IVF, aligning directly with our research objectives. The strategy was implemented across PubMed, Scopus, IEEE, and Web of Science, with detailed search strings provided in Supplementary File 1.

Eligibility criteria

This review focuses on AI applications in male infertility, particularly in the context of IVF. While the primary inclusion criterion was relevance to assisted reproductive technologies (ART), some studies on fundamental sperm analysis techniques, such as Computer Assisted Sperm Analysis (CASA) technologies, were included due to their critical role in sperm assessment, which directly impacts ART outcomes.

Inclusion criteria:

- Studies focused on applying AI in male infertility within the context of IVF.
- Studies examining AI models that report performance metric (e.g., ROC, AUC, accuracy, precision).

Exclusion criteria:

- Studies lacking full-text availability.
- Letters, short communications, notes, reports, books, book chapters, case reports, reviews, commentaries, and editorials.

Study selection

All identified records were imported into EndNote (version 21.3) for reference management, where duplicates were removed both automatically and manually. Two independent authors screened the titles and abstracts of the retrieved papers. Full-text papers of potentially relevant studies were then assessed for eligibility. Disagreements were resolved through discussion or by consulting a third author. The study selection process is illustrated in Fig. 1.

Data extraction

A data extraction form was developed and pilot-tested. Two authors independently extracted data on study characteristics (author, year, country, objectives), population characteristics (male infertility conditions, sample size), intervention details (machine learning algorithms, assessment metrics, data types), and measured outcomes and main results. Discrepancies were resolved through discussion or by consulting a third author.

Data synthesis

The data synthesis from the included studies summarized key findings on the application of AI in male infertility within the context of IVF. This process involved categorizing AI techniques, their applications, and the reported outcomes. Categories for AI applications (e.g., Sperm Characteristics, Non-Obstructive Azoospermia, Varicocele, Normospermia, SDF, Perceived Health of Men) were defined inductively based on the primary aspects of male infertility addressed in the studies, as identified through their objectives and reported outcomes. This categorization emerged from a content analysis of the 14 included studies, where two authors independently reviewed the data to identify recurring themes (e.g., sperm morphology analysis, sperm retrieval prediction). These initial categories were then validated through an iterative process involving discussion among the research team to ensure consistency, relevance to the IVF context, and alignment with the study's aim of mapping AI applications. Discrepancies were resolved by consensus or consultation with a third author, confirming the robustness of the categorization scheme.

We employed content analysis to summarize and report results based on study objectives, organizing the findings in a structured format using tables and graphs. This approach visualizes the breadth of research in the field and highlights research gaps, providing a clear framework for understanding how AI is applied to male infertility management in IVF.

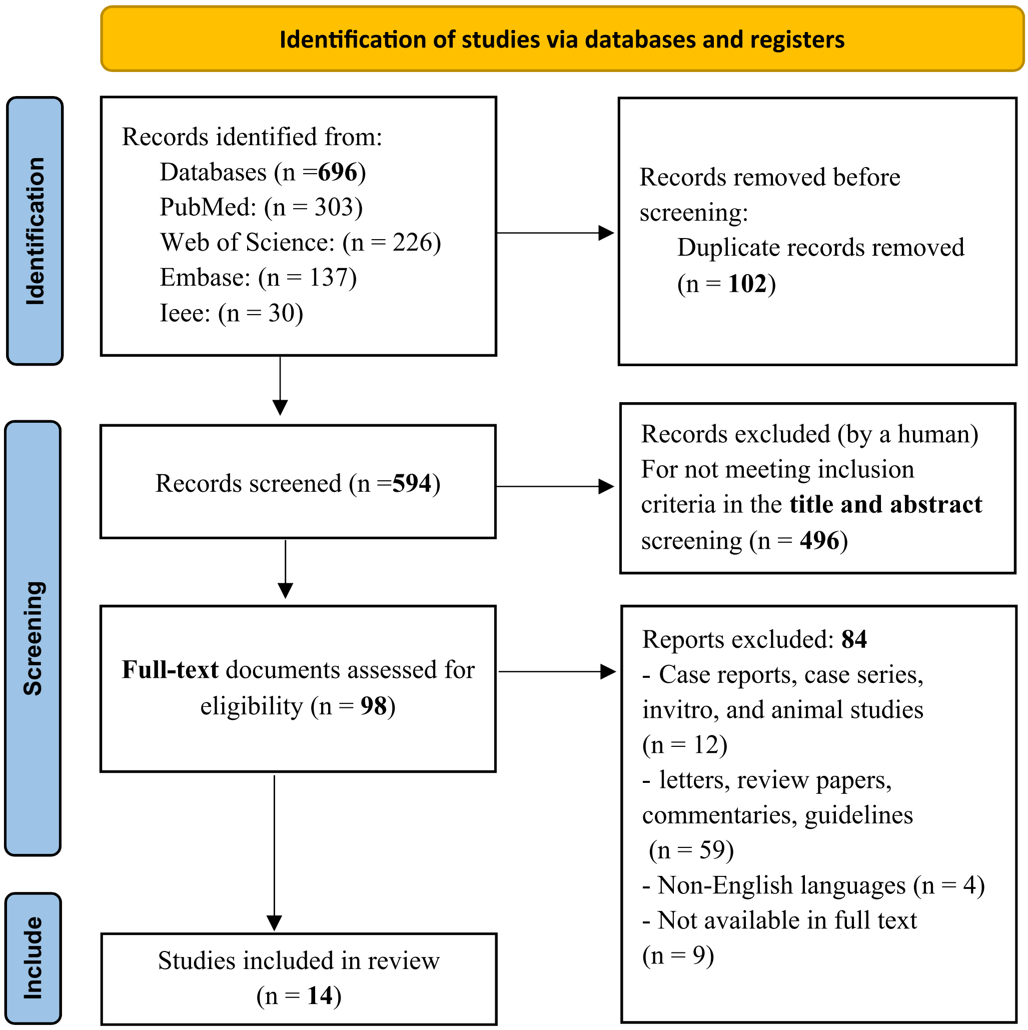

Fig. 1 The PRISMA flowchart (2020)

Results

Selection and characteristics

The search identified 696 records. After removing duplicates, 402 records were screened by title and abstract, leading to the selection of 18 articles for full-text review. From these, 14 met the inclusion and exclusion criteria and were included in the study, as detailed in Table 1. All included studies were assessed for relevance to IVF, with the primary focus on AI applications directly supporting IVF processes, such as sperm selection for ICSI, prediction of IVF outcomes, and treatment optimization (e.g., varicocele repair impacting IVF success). Some studies, such as those involving CASA technologies, focus on foundational sperm analysis (e.g., morphology and motility assessment) rather than direct IVF outcomes. These were included because accurate sperm evaluation is a critical step in IVF, influencing sperm selection and fertilization success, thus providing indirect but essential relevance to the IVF context.

The AI applications identified in the studies were categorized into six primary groups based on the aspect of male infertility being addressed:

1. **Sperm Characteristics** [20–23]**:** Evaluation of sperm morphology and motility using image analysis; assessment of sperm quality and identification of abnormal sperm characteristics; classification of sperm into different categories based on morphology and motility.
2. **Non-Obstructive Azoospermia** [24–28]**:** Prediction of sperm retrieval success in NOA patients; analysis of testicular histology images to identify viable sperm.
3. **Varicocele** [29]**:** Diagnosis and grading of varicocele using imaging techniques; prediction of post-surgical

Table 1 Study characteristics and data extracted from the included studies

Author/ Ref	Country/ Year	Aim	Specific variables	Problem/disease	Data type	Dataset	Output/class	AI models	Performance indicators
Yi, W. J. [31]	South Korea / 1998	Classify sperm according to the characteristics of their head	Sperm morphology	Male reproducible health and fertility	Image	Images of semen specimens from 12 males (25–30 sample images for each person)	1 Normal group and 3 abnormal groups (elongated (tapering), a small, a megalo and an amorphous one according to its size, shape and the existence of defects)	ANN-Multi-Layer Perceptron (MLP)—in the two hidden-layer MLPs: 70 neurons in the first hidden layer / 60 in seconf hidden layer	ACC for 4 Groups-0.822 0.792 0.837 0.807
Wald, M. [24]	USA / 2005	IVF/ICSI outcome prediction	IVF/ICSI attributes	Obstructive (OA) and non-obstructive (NOA) azoospermia	Clinical data	113 IVF/ICSI cycles (derived from patients who underwent IVF/ICSI with SRS)	IVF/ICSI induced intrauterine pregnancies	Linear /quadratic discriminant function analysis (LDFA/ QDFA), logistic regression, and neural network	AUC 4-hidden node neural network- 0.783 LDFA-0.163 QDFA-0.000 logistic regression-0.575
Goodson, S. G. [32]	USA / 2017	Classify all patterns of human sperm motility during in vitro capacitation following the removal of seminal plasma	Sperm motility	NA	Video	2817 sperm from 18 individuals	Five classes based on their kinematic parameters (classified as progressive, intermediate, hyperactivated, slow, or weakly motile)	Support vector machine (SVM)-based decision tree	ACC-89.9%
Hafiz, P. [20]	Iran / 2017	Predicting implantation outcome of IVF/ ICSI or the chance of pregnancy	IVF/ICSI attributes	Infertility	Clinical data	The IVF/ICSI dataset contains 29 variables of 486 patients	Positive and negative implantations	Support vector machine (SVM), recursive partitioning (RPART), random forest (RF), adaptive boosting, and one-nearest neighbor	AUC (%)—Accuracy (%) SVM 57.57—68.3 Adaboost 47.52—66.99 RPART 82.05—83.56 RF 84.23—83.96 1NN 50—64.84
Mirsky, S. K. [21]	Israel / 2017	Analysis of sperm cells based on the quantitative phase maps acquired through use of interferometric phase microscopy (IPM)	Sperm morphology	Infertility	Image	1400 human sperm cells from 8 donors and described by 886 image features	Good and bad morphology	Support vector machine (SVM)	AUC—88.59% precision-recall curve (PRC)—88.67% precision—90%

Table 1 (continued)

Author/ Ref	Country/ Year	Aim	Specific variables	Problem/disease	Data type	Dataset	Output/class	AI models	Performance indicators
Zeadna, A. [25]	Israel / 2020	Prediction of the presence or absence of sperm in testicular biopsy in NOA patients	Characteristics of NOA patients	Non-obstructive azoospermia	Clinical data	119 patients who underwent TESE in a single IVF	Presence or absence of sperm in testicular biopsy	Ensemble machine-learning models (gradient-boosted trees (GBTs) and random forest) univariate and multivariate binary logistic regression models	Model AUC accuracy (%) Sensitivity (%) Specificity (%) Logistic regression (MvLRM)* 0.75—77.50—97—25 Single classification tree 0.651—64.70—78—39 Random forest (RFM) 0.755—75.6—87—54 Gradient-boosting trees (GBT) 0.807—77.3—91—51 Single classification tree using CMM** over GBT model 0.799—79.83—80.68—77.42
Gunderson, S. J. [30]	Argentina / 2021	predict successful conventional IVF in normospermic patients	Sperm PH	Normospermic patients	Clinical data	Spermatozoa from 76 IVF patients	Successful or fail conventional IVF	Gradient-boosted machine-learning algorithm	ACC—0.72 AUC—0.81 sensitivity—0.65 specificity—0.80
Sukhikh, G. T. [26]	Russia / 2021	analyzing the spectral characteristics of seminal plasma and a sperm fraction determine regularities in the transmission spectrum of microstructural waveguides filled with sperm and seminal plasma of men with normozoospermia	Characteristics of the sperm fraction and seminal plasma	Males with various disorders of spermatogenesis	-Tabular data -wave	Spectral characteristics of 345 isolated spermatozoal samples and 209 seminal plasma samples	"Norm" and "pathology"	Artificial neural network—multilayer perceptron (the number of neurons in the hidden layers is 128, 20, 10, 2)	ACC—100%

Table 1 (continued)

Author/ Ref	Country/ Year	Aim	Specific variables	Problem/disease	Data type	Dataset	Output/class	AI models	Performance indicators
Wu, D. J. [27]	USA / 2021	Locating and identifying sperm cell(s) in human testicular biopsy	Sperm location in images from testicular biopsy samples	NOA	Image	702 de-identified images from testicular biopsy samples of 30 patients	Identify and locate individual sperm cells	Deep neural network: 1- MobileNetV2 was used as a feature extraction network, 2- single-shot detector (SSD) was used as an object detection network	Mean average precision (mAP)—0.741 average recall (AR)—0.376
Lee, R. [28]	Canada / 2022	Detect rare human sperm in semen and microsurgical testicular sperm extraction (micro-TESE) samples using bright-field (BF) microscopy	Sperm location in images from testicular biopsy samples	Normospermic and nonobstructive azoospermia patients	Image	35,761 bright-field (BF) microscopy image patches with fluorescent ground truth image to pairs segment sperm	Identify and locate individual sperm cells	Convolutional neural network based on the U-Net architecture	Precision (positive predictive value [PPV])—91%, recall (sensitivity)—95.8%, and F1-score—93.3%
Liu, G. [33]	China / 2022	Characterize morphology of freely swimming human sperms	Sperm morphology	NA	Image	NA	Sperm head detection	Deep learning-one-stage YOLOv3-tiny	Dice score of 0.948 in sperm head segmentation precision of 0.940, a recall of 0.962, and a F1-score of 0.951
Ory, J. [29]	US-Canada / 2022	Predict which men with varicocele will benefit from treatment predicting upgrade in sperm concentration	Sperm count	Varicocele	Clinical data	Data from 240 men	3 classes: improve, equivocal, and unlikely to improve	Random forest model	AUC—0.72

Table 1 (continued)

Author/ Ref	Country/ Year	Aim	Specific variables	Problem/disease	Data type	Dataset	Output/class	AI models	Performance indicators
Jiang, X. [23]	China / 2023	Predicting the unexpected total fertilization failure in conventional IVF cycles	Semen parameters	Infertility	Clinical data	19,539 cycles that received their first IVF treatments	Occurrence of TFF in the first IVF cycles	Least Absolute Shrinkage and Selection Operator (LASSO) Extreme Gradient Boosting (Xgboost)	AUC—LASSO—0.74 AUC—Xgboost—0.75 without semen parameters: AUC—LASSO—0.72 AUC—Xgboost—0.73 with semen parameters: AUC—LASSO—0.58 AUC—Xgboost—0.57 refitted models: AUC—LASSO—0.72 AUC—Xgboost—0.69 the event net reclassification index (NRI) – 5.20 for the LASSO model and – 0.71
Peng, T. [12]	China / 2023	identify the combined effect of the DNA fragmentation index (DFI) and conventional semen parameters on IVF outcomes classify participants into several coexposure pattern groups	Semen parameters (+ DNA fragmentation)	Sperm DNA fragmentation	Clinical data	1258 couples undergoing fresh transfer IVF cycles	Cluster 1 (low sperm DFI values and high sperm motility and semen concentration levels), Cluster 2 (low sperm DFI values and moderate sperm motility and semen concentration levels), Cluster 3 (low sperm DFI values and low sperm motility and semen concentration levels) and Cluster 4 (high sperm DFI values and low sperm motility and semen concentration levels)	Unsupervised K-means clustering method	Compared with those in Cluster 1, participants in Cluster 3 and Cluster 4 had lower odds of a live birth outcome, with odds ratios (0.733 and 0.620)

outcomes for varicocele patients impacting IVF success.

4. **Normospermia** [28, 30]**:** Analysis of normospermic samples to identify subtle abnormalities; prediction of IVF outcomes based on normospermic parameters.
5. **Sperm DNA Fragmentation** (SDF) [12]**:** Assessment of sperm DNA integrity using AI-driven techniques; prediction of fertilization potential based on DNA fragmentation levels.
6. **Perceived Health of Men** [31]**:** Analysis of lifestyle, environmental, and socio-demographic factors impacting male fertility; prediction of infertility risk based on perceived health metrics relevant to IVF planning.

These categories reflect both direct IVF applications (e.g., outcome prediction, sperm selection) and indirect contributions (e.g., sperm quality assessment via CASA) that enhance IVF efficacy. Detailed study characteristics are presented in Table 1, with AI applications and their interconnections further illustrated in Fig. 2.

Data utilized for machine learning analysis

The artificial intelligence primarily analyzed clinical data [12, 20, 22–25, 30], but it also utilized images [21, 27, 28, 31, 33] and video data [32]. Additionally, one study focused on tubular data waves [26].

Machine learning techniques

Machine learning techniques such as MLP [31], SVM [20, 21, 32], Logistic Regression [24, 25], Random Forest [20, 22, 25] and Gradient Boosting Trees [25, 30], LASSO [23], XGBoost [23], and Neural Network [24, 26–28] on sperm images of infertile patients to investigate sperm-related factors such as sperm head morphology, sperm motility, pH and its quality were used.

Applications of AI in male infertility

AI has facilitated the classification of sperms based on morphology [21, 31, 33], mobility [12, 32], concentration [12, 25, 29], and fraction [26]. It has also been used to predict implantation and IVF outcomes [20, 23, 24, 30],, as well as to identify and locate sperms [27, 28]. The chart outlines the research and publication trends regarding the application of AI in addressing male infertility in IVF, with the first publication in 1998. A peak in publications occurred in 2017, followed by a significant increase from 2021 onward, indicating growing interest and advancements in this field.

Figure 3 highlights the adoption of AI solutions for male infertility problems in IVF across different countries. The USA leads in implementation (29%), followed by China (21%) and Israel (14%). This data reflects the global interest in leveraging AI to enhance fertility treatments.

Figure 4 illustrates the trend of AI research publications on infertility from 1998 to 2023, with the x-axis representing the publication years (1998, 2005, 2017, 2021, 2022, and 2023) and the y-axis indicating the number of studies published each year. The data reveals a modest start with just one study published in both 1998 and 2005, followed by a peak in 2017 with four studies, reflecting a surge in research activity. From 2021 to 2022, the number of studies stabilizes at three per year, before declining to two in 2023. This trend highlights a significant increase in AI-related infertility research over the past decades, though activity has slightly tapered off in recent years.

To improve understanding and analysis of AI's role in diagnosing male infertility issues in IVF and supporting treatment, the study provides collected data from the included studies in Fig. 2. This diagram systematically organizes machine learning algorithms, their evaluation metrics, patient-related data types, study objectives, male infertility diseases or conditions, as well as the causes and factors contributing to infertility.

Tables 2, 3, and 4 present key findings of AI models in analyzing sperm-related factors, including sperm motility, morphology, semen quality, and sperm localization in biopsy samples.

1. AI-driven analysis of sperm-related factors

   This table highlights the superior performance of machine learning and deep learning models, such as SVM, MLP, and YOLOv3-tiny, in assessing sperm parameters compared to traditional methods. For instance, the SVM model achieved an AUC of 88.59% and a precision of 90% in sperm morphology classification, making it a powerful tool for infertility diagnosis. Additionally, RF and Recursive Partitioning models demonstrated the best performance in predicting IVF/ICSI implantation success, whereas Adaboost showed poor predictive capability (Table 2).
2. AI-based prediction of fertilization failure
   The results indicate that unsupervised K-means clustering, which analyzes SDF, identifies a strong correlation between IVF failure and sperm parameters. Specifically, couples with high DNA fragmentation and low sperm motility had significantly lower IVF success rates, with odds ratios for live birth at 0.733 (Cluster 3) and 0.620 (Cluster 4) (Table 3).
3. Prediction and localization of sperm in non-obstructive azoospermia
   This section evaluates the effectiveness of advanced machine learning and deep neural network models

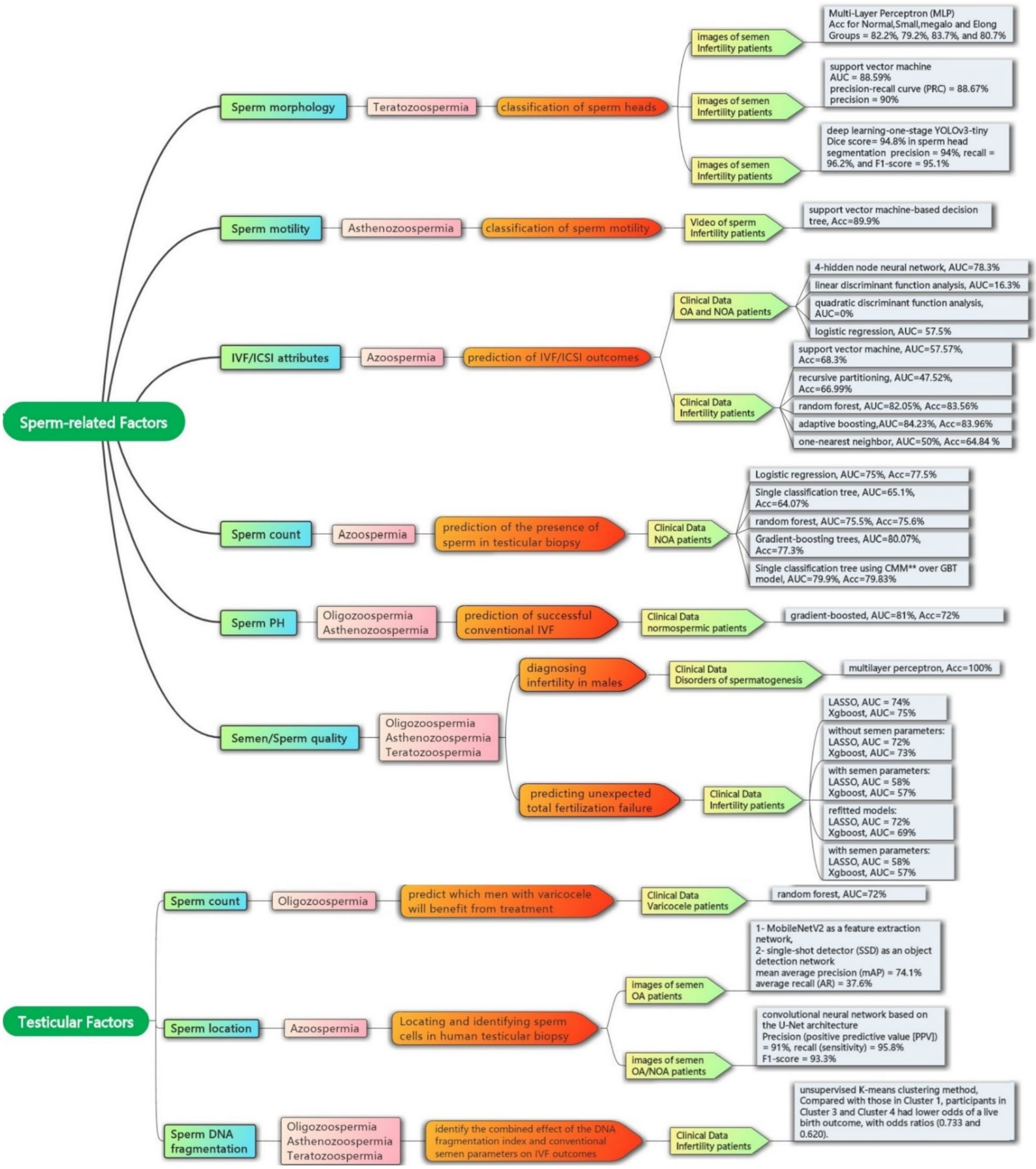

Fig. 2 Fllowchart of AI applications in male infertility within the IVF Context. This flowchart categorizes AI applications identified in the included studies, illustrating their specific uses and interconnections within IVF. Starting with broad categories (e.g., Sperm Characteristics, Non-Obstructive Azoospermia), it branches into specific applications (e.g., morphology analysis, sperm retrieval prediction) and shows how they contribute to IVF outcomes (e.g., improved sperm selection, enhanced success rates). Arrows indicate relationships, such as how sperm quality assessment supports outcome prediction, providing a clear overview of AI's role in male infertility management

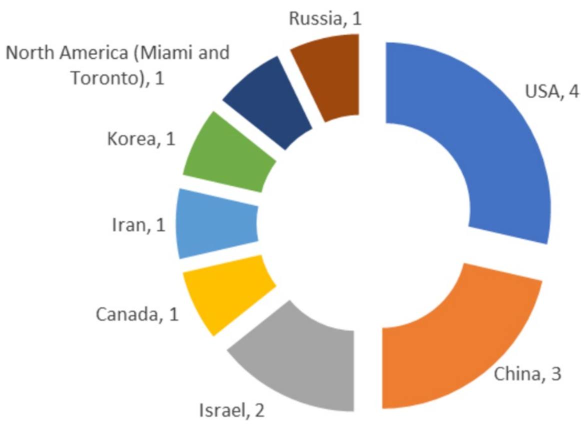

Fig. 3 Geographical distribution of studies on AI applications in male infertility. This heatmap illustrates the global distribution of the 14 included studies, with color intensity representing the number of studies per country (e.g., darker shades for higher numbers). The USA leads with 29% of studies, followed by China (21%) and Israel (14%), reflecting significant research activity in these regions. This visualization highlights the concentration of AI research in male infertility across different countries, emphasizing areas of focus and potential gaps in global representation

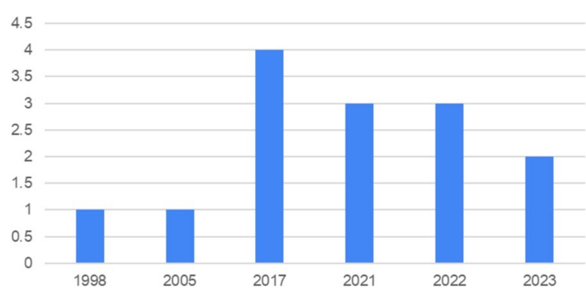

Fig. 4 Publication trend of AI research on male infertility (1998–2023)

in detecting sperm within testicular biopsy samples. The GBT model outperformed others in predicting sperm retrieval success in NOA patients, achieving 91% sensitivity and an AUC of 0.807. Additionally, deep CNN-based U-Net architecture achieved 91% precision and an F1-score of 93.3%, demonstrating high accuracy in identifying rare sperm within NOA biopsy (Table 4).

Most of the studies (10 out of 14) concentrate on sperm-related issues, including aspects such as sperm presence and quality (morphology, count, motility). Furthermore, four articles have explored male infertility issues originating from testicular causes.

Utilizing machine learning techniques such as MLP, SVM, and deep neural network on images of sperm from patients with infertility was employed for classifying sperm *head morphology* (*shape and structure*) in semen analysis. Machine learning methods like SVM-based Decision Tree on videos of sperm from infertility patients for analyzing *sperm motility (ability to swim),* boasting an accuracy of 89.9%, have the potential to assist in male fertility assessments.

Machine learning techniques were applied to improve both outcomes and efficiency of IVF and ICSI procedures. Algorithms such as the 4-hidden node neural network (which achieved the highest AUC value of 78.3%), LDFA, QDFA, and logistic regression were utilized for patients diagnosed with obstructive azoospermia (OA) or non-obstructive azoospermia (NOA). SVM, Adaboost (with the highest AUC value of 84.23%), RPART, RF, and 1NN were also applied to infertility patients. These algorithms facilitated the development of predictive models, which assess the likelihood of successful fertilization or embryo implantation based on various patient and treatment parameters.

Machine learning was used to evaluate semen quality and identify male fertility issues, including predicting total fertilization failure in IVF procedures. Classification algorithms like multilayer perceptron were applied for individuals with spermatogenesis disorders, while predictive models such as LASSO and XGBoost utilized semen parameters to diagnose infertility in male patients. A gradient boosted model on normospermic patients, achieving an AUC of 81%, used sperm pH for forecasting IVF success.

Utilizing machine learning methods like Logistic regression, Single classification tree, Random forest, and Gradient-boosting trees (with the highest AUC value of 80.07%), as well as Single classification tree using CMM over GBT model (which achieved the highest accuracy value of 79.83%) for patients diagnosed with NOA, was employed to analyze *sperm count.* Random Forest model, achieving an AUC of 72%, is utilized to examine *sperm count* in individuals affected by varicocele, a prevalent condition marked by the enlargement of veins in the scrotum.

Deep neural networks were utilized on images of individuals diagnosed with obstructive azoospermia or non-obstructive azoospermia to detect and recognize sperm cells within human testicular biopsy samples. Also, the K-means clustering method, an unsupervised machine learning approach, is utilized to examine SDF and its association with testicular factors in data from patients experiencing infertility.

Discussion

This systematic review examines the application of artificial intelligence in male factor infertility by analyzing 14 relevant studies. The findings highlight that machine learning techniques, including multi-layer perceptrons

Table 2 AI-Driven analysis of sperm-related factors in male infertility

	AI model	Performance metric	Dataset size	Key FindIngs
Sperm motility	SVM-based decision tree	Accuracy: 89.9%	2817 sperm (18 individuals)	High accuracy in classifying sperm motility patterns during capacitation
Sperm morphology	ANN-MLP	Accuracy: 0.822, 0.792, 0.837, 0.807	25–30 images/person (12 males)	Effective classification of sperm head morphology for fertility assessment
	SVM	"AUC: 88.59%, Precision: 90%"	1400 sperm (8 donors)	High accuracy in distinguishing sperm morphology for infertility diagnosis
	Deep learning (YOLOv3-tiny)	Dice: 0.948, Precision: 0.940, Recall: 0.962, F1: 0.951	Not specified	Accurate segmentation and characterization of sperm morphology
Sperm count	Random forest	AUC: 0.72	240 men	Predicts which men benefit from varicocele repair, with moderate accuracy
Sperm pH	Gradient-boosted machine learning	"AUC: 0.81, Accuracy: 0.72, Sens: 0.65, Spec: 0.80"	76 IVF patients	Sperm pH predicts IVF success with good accuracy in normospermic patients
Semen/sperm Quality	Support Vector Machine (SVM)	"AUC: 57.57%, Accuracy: 68.3%"	486 patients	Moderate performance in predicting IVF/ICSI implantation outcomes
	Recursive Partitioning (RPART)	"AUC: 82.05%, Accuracy: 83.56%"		Good performance in predicting IVF/ICSI implantation outcomes, using variable importance
	Random Forest (RF)	"AUC: 84.23%, Accuracy: 83.96%"		Best performance among models, effectively predicting IVF/ICSI outcomes with high accuracy
	Adaptive Boosting (Adaboost)	"AUC: 47.52%, Accuracy: 66.99%"		Poor performance in predicting IVF/ICSI implantation outcomes
	One-Nearest Neighbor (1NN)	"AUC: 50%, Accuracy: 64.84%"		Low performance in predicting IVF/ICSI implantation outcomes
	LASSO, XGBoost	"AUC: 0.74 (LASSO), 0.75 (XGBoost)"	19,539 IVF cycles	Semen parameters modestly improve TFF prediction, but overall accuracy is moderate
Seminal plasma & sperm characteristics	ANN-MLP (128, 20, 10, 2 neurons)	Acc: 100%	345 sperm + 209 plasma samples	Perfect classification of norm vs. pathology using spectral data

Table 3 AI-driven analysis of sperm DNA fragmentation in male infertility

AI model	Performance metric	Dataset size	Key findings
Unsupervised K-means clustering	Odds ratios for live birth: 0.733 (Cluster 3), 0.620 (Cluster 4)	1258 couples	Clusters with high DNA fragmentation and low motility reduce IVF success

(MLP), support vector machines, logistic regression, random forests, and deep neural networks, effectively predict IVF outcomes based on sperm-related factors such as morphology, motility, pH, and quality. AI plays a crucial role in managing male infertility through applications like sperm classification, outcome prediction, and treatment optimization, offering advantages over routine methods in reproductive health [34, 35].

Compared to traditional manual semen evaluation, which is time-consuming, subjective, and prone to inter-observer variability [9], AI-driven methods demonstrate significant improvements. For instance, Hicks et al. (2019) emphasized that machine learning reduces

Table 4 AI-driven analysis of sperm count & sperm location in male infertility

	AI Model	Performance metric	Dataset Size	Key findings
Non-obstructive Azoospermia (NOA)—Sperm Prediction in Testicular Biopsy	Ensemble models (GBT, RF), logistic regression, single classification tree	"AUC: 0.807 (GBT), Acc: 77.3%, Sens: 91%, Spec: 51%"	119 patients (TESE cycles)	Gradient-boosted trees (GBT) outperform with high sensitivity for sperm detection in NOA
	Linear/quadratic discriminant, logistic regression, neural network	"AUC: 0.783 (neural network)"	113 IVF/ICSI cycles	Neural network best predicts IVF/ICSI success with surgically retrieved sperm
Non-obstructive Azoospermia (NOA)—Sperm Location in Testicular Biopsy	Deep CNN (MobileNetV2 + SSD)	mAP: 0.741, AR: 0.376	702 images (30 patients)	Effective sperm detection in NOA biopsy images, though recall needs improvement
	CNN (U-Net architecture)	Precision: 91%, Recall: 95.8%, F1: 93.3%	35,761 + 7663 + 7985 patches	High accuracy in detecting rare sperm in NOA samples using bright-field microscopy

variability in sperm analysis, with studies in our review (e.g., SVM achieving 88.59% AUC for morphology classification, ref 15) outperforming manual assessments that typically achieve lower reproducibility (accuracy often < 80% due to human error) [9]. Similarly, AI-based predictive models, such as random forests (AUC 84.23%, ref 14), surpass conventional statistical methods like logistic regression (AUC often < 70% in traditional IVF outcome studies) by integrating multiple parameters (e.g., sperm quality, clinical data) for higher accuracy and efficiency [36].

CASA technologies, while advanced, remain limited by sample quality issues (e.g., debris interference), whereas AI-enhanced CASA (e.g., YOLOv3-tiny, F1-score 0.951, ref 28) offers superior precision and automation, directly benefiting IVF sperm selection. However, AI methods require large datasets and may introduce algorithmic biases, contrasting with routine methods' reliance on operator experience, which, while less data-intensive, lacks consistency [37].

Translating these AI applications into clinical practice holds transformative potential, particularly for underserved regions. AI-powered sperm analysis tools can automate diagnostics, reducing the need for highly trained specialists and expensive equipment, which are scarce in low-resource settings. For example, portable AI-driven microscopy systems could enable rapid sperm quality assessment in rural clinics, lowering costs and improving access to IVF [38].

Integrating AI with telemedicine platforms could facilitate remote consultations, allowing specialists to guide treatment planning in regions lacking fertility centers [38]. Pilot studies in telemedicine for infertility care have shown promise in Africa and South Asia, where AI could bridge gaps in expertise and infrastructure [39, 40]. However, challenges such as internet access, model generalizability across diverse populations, and regulatory approval must be addressed to ensure equitable deployment.

Despite these promising findings, the reviewed studies exhibit potential biases that warrant consideration. Many rely on small sample sizes (e.g., 76 patients in [30], 119 in [25]), which may limit statistical power and external validity. Retrospective data collection, common across the studies (e.g., [20, 23]), introduces selection bias, as historical data may not reflect current patient demographics or treatment protocols. Furthermore, most models were trained on specific populations (e.g., US, China, Israel), raising concerns about applicability to diverse ethnic or socioeconomic groups. These biases, echoed in the Limitations section, suggest that findings should be interpreted cautiously, with future research prioritizing larger, prospective, and multi-center studies to enhance robustness and generalizability.

Emerging AI trends offer exciting implications for IVF and male infertility management. Integration with genomic data, a gap noted in our review, could revolutionize outcome prediction by identifying genetic markers linked to sperm quality or IVF success (e.g., whole-genome sequencing to detect mutations affecting spermatogenesis). Real-time sperm analysis, enabled by advancements in deep learning and microscopy (e.g., [33]'s YOLOv3-tiny), could allow dynamic monitoring during IVF procedures, improving sperm selection precision over static CASA methods. These trends, though underrepresented in the current literature, promise personalized treatment plans and higher success rates, though they require validation and infrastructure investment to reach clinical maturity.

Evaluating sperm morphology remains essential for successful ART, and AI technologies represent a significant step toward standardized, accurate assessments [34]. Our review demonstrated effective applications in assessing testicular factors (e.g., NOA sperm retrieval, AUC 0.807 [25]), identifying sperm in biopsies, and evaluating SDF, a key infertility cause linked to oxidative stress and abnormal spermatogenesis [38]. In varicocele management, AI models (e.g., random forest, AUC 0.72 [29]) outperform traditional nomograms by predicting post-surgical semen improvements, avoiding unnecessary interventions [41]. SDF diagnosis, critical for sperm quality, is enhanced by AI-driven clustering (e.g., K-means [12]), which traditional assays struggle to standardize. These advancements underscore AI's potential to address limitations in routine methods, though clinical validation remains essential.

This review highlights AI's significant potential in male infertility within the IVF context, improving diagnostic accuracy, treatment selection, and predictive capabilities. Integrating AI into clinical workflows could revolutionize care by providing precise, personalized solutions, particularly in underserved regions. However, challenges persist, including standardizing methodologies, addressing biases, and validating models in real-world settings. Future research should explore genomic integration, real-time analysis, and hybrid AI-expert systems to further enhance IVF outcomes, building on the comparative advantages over traditional approaches demonstrated here.

Ethical and practical considerations

AI is transforming reproductive health, particularly in male infertility and IVF, by offering significant advantages but also introducing ethical challenges. While clinical issues like patient privacy and bias—discussed in the Conclusion—are key concerns, broader societal implications require attention.

One major issue is access to AI-powered fertility treatments. Due to high costs and technical demands, these advancements are primarily available in affluent regions such as the US, China, and Israel, creating disparities in reproductive care. This geographic limitation can also affect AI model performance, as systems trained on data from these regions may not be as effective in areas like Africa or South America. Such imbalances risk widening existing healthcare inequalities. Portable AI solutions may offer some relief, but comprehensive global policies are essential to ensure fair distribution.

Data quality and bias also impact AI reliability. Smaller datasets, such as those with only 76 patients, are less dependable than larger ones containing tens of thousands of images. Moreover, non-diverse or retrospective datasets can introduce biases, leading to inaccurate predictions for different demographic groups. To enhance AI fairness and effectiveness, diverse, large-scale datasets from various populations are needed.

Another ethical risk involves potential misuse for selective reproduction. AI's ability to analyze genetic markers beyond fertility could allow parents or clinics to prioritize certain traits, raising concerns similar to those in genetic screening debates. To prevent this, strict regulations must confine AI applications to infertility treatment rather than trait selection.

The psychological effects of AI predictions are also noteworthy. If an AI system forecasts a low chance of IVF success, it may increase stress and influence reproductive decisions, such as opting for donor sperm. Over-reliance on AI might also undermine human judgment, leaving couples feeling disconnected from their choices. Therefore, clinicians should integrate AI insights with supportive counseling to preserve emotional well-being.

Data privacy and ownership present another challenge. AI processes highly sensitive reproductive data, including sperm analysis, medical histories, and genetic profiles. Without strong safeguards like encryption, this data could be at risk of breaches or commercial exploitation by clinics and tech companies. Furthermore, the question of data ownership remains unresolved—should control rest with patients, clinics, or AI developers? Addressing these concerns requires clear legal frameworks to ensure informed consent and protect patient autonomy.

Regulatory barriers further slow AI adoption in fertility clinics. Agencies like the FDA and EMA enforce strict safety and accuracy standards, but the lengthy approval processes can be costly and burdensome, particularly for smaller clinics in underserved areas. While regulations are necessary for patient safety, more streamlined approval pathways could help balance oversight with timely access to AI innovations.

Lastly, accountability in AI-driven fertility decisions must be addressed. If AI errors lead to negative outcomes—such as incorrect sperm selection—it is unclear whether responsibility falls on developers, clinicians, or both. Establishing transparent AI systems and legal guidelines is essential to define liability.

Tackling these ethical concerns—including accessibility, misuse, psychological effects, data security, and accountability—will ensure AI-driven reproductive healthcare remains equitable and responsible. Future research and policy development must focus on these issues to guide ethical implementation.

Limitations

This study has several limitations. First, the included studies used a variety of AI techniques, data sources, and applications in the field of male infertility. This heterogeneity made it challenging to draw definitive conclusions and compare the performance of different AI models in studies. Second, this review included only 14 eligible studies, which may not provide an overview of AI applications in male infertility. The relatively small number of studies limits the ability to generalize the findings. Two of the researches are old, which makes their data obsolete and not really applicable to current era. Times have changed, techniques, devices and therapies as well as patient population and indications have changed and these factors affects outcomes. Last, the included studies focused primarily on short-term outcomes, such as sperm classification and selection. The long-term impact of AI-based interventions on fertility outcomes and patient-reported measures is not well established.

Many reviewed studies are limited by small sample sizes and retrospective data collection, which may introduce selection biases and limit external validity. Most AI models have been trained on specific populations, raising concerns about their applicability across diverse patient demographics. To enhance reliability, future research should focus on large-scale, prospective studies with diverse datasets to ensure AI models are robust and widely applicable.

Conclusion

Traditional semen analysis and infertility diagnosis rely on manual methods. These include semen assessment, motility grading, and biochemical assays. They vary between observers and depend on expertise, leading to uneven IVF outcomes. AI-driven approaches improve this. They offer better accuracy, consistency, and speed. For example, machine learning in CASA ensures steady sperm classification. Deep learning for sperm selection boosts ICSI success (e.g., F1-score 0.951 [28]). Predictive models, like random forests (AUC 84.23% [14]), top traditional stats using patient data well. Yet, AI needs large datasets and faces bias and regulatory hurdles.

To integrate AI into clinical workflows, specific steps are key. First, create standardized protocols for data collection. This ensures AI tools, like sperm analysis software, work consistently across clinics. Second, train clinicians to use AI systems. Short courses on interpreting AI outputs can bridge skill gaps. Third, align with regulators. Seek approvals from bodies like the FDA or EMA to certify AI tools for IVF use. For underserved regions, deploy portable AI devices and link them to telemedicine. This cuts costs and boosts access.

Ethical issues matter too. Protect patient data with encryption and strict access rules. Ensure informed consent by explaining AI's role and limits to patients. Address bias by training models on diverse datasets, covering varied ethnic and economic groups. Transparent AI decisions—showing how predictions are made—build trust.

Future research should grow stronger. Multicenter trials can validate AI across regions. This tests models like SVM or CNN in diverse groups, ensuring wide use. AI-driven sperm selection can enhance IVF and ICSI. Standardizing AI methods is key. Unified approaches for data and models will speed clinical adoption. These steps can make AI precise and personal. They raise IVF success for couples worldwide.

AI can improve male infertility diagnosis and treatment in IVF. Future work should validate models with large trials. Standard protocols will aid adoption. Hybrid models mixing AI and expert input may lift results. With these steps, AI can offer precise, personal solutions. This raises IVF success for couples worldwide.

Abbreviations

ACC	Accuracy
AI	Artificial Intelligence
ANN	Artificial Neural Network
ART	Assisted Reproductive Technologies
AUC	Area Under the Curve
CASA	Computer Assisted Sperm Analysis
CNN	Convolutional Neural Network
EMA	European Medicines Agency
FDA	Food and Drug Administration
GBT	Gradient Boosting Trees
ICSI	Intracytoplasmic Sperm Injection
IUI	Intrauterine Insemination
IVF	In Vitro Fertilization
LASSO	Least Absolute Shrinkage and Selection Operator
MLP	Multi-Layer Perceptron
NOA	Non-Obstructive Azoospermia
OA	Obstructive Azoospermia
RF	Random Forest
SDF	Sperm DNA Fragmentation
SVM	Support Vector Machine
TESE	Testicular Sperm Extraction
Xgboost	Extreme Gradient Boosting

Supplementary Information

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Additional file 1.

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Author contributions

A.B. and K.Q. designed the theoretical and empirical frameworks of the study and lead the review analysis of selected studies. R.S. performed the initial literature search and review. F.S. and M.D. performed subsequent literature review. All authors read and approved the final manuscript.

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Declarations

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