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Predictive Value of Artificial Intelligence–Assisted Blastocyst Assessment for Implantation Success and Its Agreement with PGT-A Results in Frozen Embryo Transfer Cycles

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Abstract

One of the key elements affecting the success of assisted reproductive technology (ART) is embryo selection. Implantation potential may not always be predicted by traditional morphology-based assessment techniques, which are subjective. A possible non-invasive method for enhancing embryo selection is artificial intelligence (AI)-assisted embryo evaluation. The predictive value of AI-based blastocyst assessment for implantation success and its agreement with pre-implantation genetic testing for aneuploidy (PGT-A) results in frozen embryo transfer (FET) cycles were assessed in this retrospective observational study.

Analysis was done on 345 FET cycles that followed autologous oocyte intracytoplasmic sperm injection (ICSI). Day 5 blastocysts were evaluated using both AI-derived viability assessment based on blastocyst image analysis and Gardner's morphological grading system. Serum β-hCG positive after embryo transfer was used to assess the success of implantation. The total β-hCG positive rate among 340 cycles with conclusive results was 69.7% (237/340). When compared to lower-grade embryos, higher-grade blastocysts showed noticeably better implantation results ($p = 0.001$). In a similar vein, the implantation rates of embryos classified as having a high AI viability score were considerably greater than those of embryos with a low score ($p = 0.013$). With a Cohen's kappa coefficient of 0.257, AI-assisted genetic prediction showed a fair degree of agreement with verified PGT-A results. These results imply that AI-assisted embryo evaluation could be a useful non-invasive decision-support tool for embryo selection. It could also help standardize embryo evaluation in ART practice and improve implantation outcomes.

INTRODUCTION

Infertility is a major global public health issue, defined as the inability to conceive after 12 months of regular unprotected sex. Its prevalence has risen due to factors like delayed parenthood, environmental effects, endocrine disorders, lifestyle changes, and age-related reproductive decline. The **World Health Organization (WHO)** estimates infertility affects about **one in six people** worldwide during their reproductive years. Besides fertility challenges, infertility also causes emotional, psychological, social, and financial stress for couples[1–4].

Assisted Reproductive Technology (ART), especially **In Vitro Fertilization (IVF)**, is a leading treatment for infertility. The development of **Intracytoplasmic Sperm Injection (ICSI)** has notably improved fertilization success in cases of severe male infertility and complex reproductive issues. Despite advances in ovarian stimulation, embryo culture, cryopreservation, and lab techniques, **successful embryo implantation remains a critical challenge for IVF outcomes[2–8]**.

The success of implantation and the overall results of IVF are largely dependent on the choice of embryo. Traditionally, skilled embryologists use Gardner's blastocyst grading system to evaluate embryos anatomically. Day 5 blastocysts are assessed based on trophectoderm (TE) morphology, inner

cell mass (ICM) quality, and blastocoel growth. Improved implantation and pregnancy outcomes are typically tied to embryos with optimum morphological traits[8,9–12].

However, there are a number of drawbacks to traditional morphological grading. Inter-observer variability arises from the subjective character of the judgment, which can differ amongst embryologists. Moreover, chromosomal competence and implantation potential may not be reliably predicted by morphology alone. While embryos with less-than-ideal morphology can occasionally result in healthy pregnancies, morphologically normal embryos may nonetheless have chromosomal abnormalities. These restrictions have prompted the creation of more equitable and repeatable methods for evaluating infants.[3,7,13,14].

Recent advances in Artificial Intelligence (AI) and deep learning technologies have introduced innovative possibilities in reproductive medicine. AI-assisted embryo assessment systems utilize computer vision algorithms and deep learning models to analyze high-resolution embryo images and identify subtle morphological features that may not be readily appreciated during manual microscopic examination. AI algorithms can generate embryo viability scores and predict implantation potential through automated image analysis[8,15–17].

Improved standardization, less subjectivity, increased reproducibility, and increased embryo selection efficiency are just a few possible benefits of AI-assisted embryo evaluation. Blastocoel expansion, inner cell mass shape, trophectoderm quality, and overall blastocyst integrity are just a few of the morphological criteria that deep learning algorithms can simultaneously assess. These AI-generated evaluations could help embryologists choose embryos with more chance for implantation, which could lead to better IVF results[9–10,18–19].

Pre-implantation Genetic Testing for Aneuploidy (PGT-A), which assesses the chromosomal condition of the embryo before transfer, is another significant development in contemporary reproductive medicine. Improved live birth outcomes, reduced miscarriage risk, and increased implantation rates have all been linked to the transfer of euploid embryos. Nevertheless, PGT-A is still invasive, costly, technically difficult, and necessitates embryo biopsy procedures that could compromise the integrity of the embryo[7,16].

As a result, there is growing interest in creating non-invasive methods that can forecast the genetic competence and implantation potential of embryos without requiring an embryo biopsy. Through the study of morphological picture patterns, artificial intelligence-assisted embryo assessment has shown encouraging potential as a non-invasive supplementary method for predicting embryo viability and euploidy. Therefore, combining AI-assisted embryo evaluation with traditional embryo grading should enhance embryo selection techniques while reducing invasive procedures[20].

Due to improvements in vitrification and cryopreservation techniques, frozen embryo transfer (FET) cycles have become more prevalent in modern IVF procedures. FET cycles lessen the problems brought on by ovarian hyperstimulation while improving synchronization between endometrial receptivity and embryo development. Thus, an essential clinical metric for assessing the quality of the embryo and the

effectiveness of treatment is the evaluation of implantation results after frozen embryo transfer[6,11–12,21–23].

In order to investigate the clinical efficacy of AI-aided blastocyst evaluation in improving embryo selection and implantation outcomes in cycles of assisted reproductive technology, the current retrospective observational cohort research was created. Day 5 blastocyst-stage embryos transplanted during frozen embryo transfer cycles after ICSI-based IVF procedures were examined in this study. Serum β-hCG positivity was used to determine implantation outcomes, and conventional blastocyst morphological grading, AI-derived embryo viability rating, and AI-assisted genetic competence prediction were assessed[11,23].

The evaluation of traditional blastocyst morphological assessment, AI-derived viability scoring, and AI-assisted genetic competence prediction in a homogeneous cohort made up only of Day 5 frozen embryo transfer cycles is one of the study's main strengths. In order to provide a thorough evaluation of AI's practical application, the study also assessed concordance between AI-generated genetic predictions and verified PGT-A results. Practice of Assisted Reproductive Technology[13–15, 24–25].

The results of this study could add to the increasing amount of data that supports the use of AI in reproductive medicine and further establish AI-assisted embryo assessment as a useful non-invasive clinical decision-support tool for enhancing implantation outcomes and optimizing embryo selection in assisted reproductive technology[16–17,26].

Retrospective selection of frozen embryo transfer cycles after IVF/ICSI operations is demonstrated by the workflow. Day 5 blastocysts were subjected to both AI-assisted viability/genetic scoring and traditional morphological grading based on Gardner's criteria. Serum β-hCG positivity was used to assess implantation results. Conventional morphology and AI-assisted assessment were then compared statistically to measure predictive performance and concordance.

MATERIAL AND METHODS

Study Design

In order to examine the clinical value of AI-aided blastocyst evaluation in enhancing embryo selection and implantation results in assisted reproductive technology (ART), this study was planned as a retrospective observational cohort study. The study examined clinical and embryological data from patients undergoing in vitro fertilization (IVF) cycles based on intracytoplasmic sperm injection (ICSI) and frozen embryo transfer (FET) in the past. The study's main goal was to determine how well AI-derived embryo viability and genetic competence scores predicted implantation success and the results of pre-implantation genetic testing for aneuploidy (PGT-A).

Study Population and Selection Criteria

The investigation was carried out at an assisted reproductive technology center at the tertiary level. Using institutional ART databases, embryology records, and electronic medical records, the clinical, laboratory, and embryological records of patients receiving ART treatment during the study period were retrospectively examined.

345 cycles of frozen embryo transfers were examined. 340 cycles with definitive serum β-hCG outcomes were included in the final analysis after cycles with incomplete implantation outcome data were excluded. Day 5 blastocyst-stage embryos were transferred during frozen embryo transfer cycles, and all included cycles were autologous IVF cycles using the patient's own oocytes.

Inclusion Criteria

The study comprised patients undergoing their first or second IVF cycles using intracytoplasmic sperm injection (ICSI). Analysis was limited to autologous IVF cycles using the patient's own oocytes. Included were women over 25 who were having Day 5 blastocyst-stage embryos during Frozen Embryo Transfer (FET) cycles. Gardner's blastocyst grading system was used for conventional morphological evaluation of all embryos. Grade A blastocysts were chosen for additional AI-assisted embryo evaluation and/or genetic evaluation. The final study population consisted of cycles with conclusive serum β-hCG implantation outcome data that could be analyzed.

Exclusion Criteria

To ensure consistency in the fertilization process, conventional IVF cycles were not included in the study. To guarantee uniformity of the embryo developmental stage and transfer procedure, fresh embryo transfer cycles, cleavage-stage embryos, compacting embryos, and Day 6 blastocysts were also excluded. Embryos with poor picture quality for AI analysis and donor oocyte cycles were excluded. Final analysis did not include cycles with conclusive serum β-hCG implantation outcome data or those with incomplete embryological or clinical records. Aneuploid embryos were not considered for embryo transfer or implantation outcome evaluation in individuals receiving PGT-A.

Embryo Assessment Protocol

Embryo Assessment Protocol
Gardner's blastocyst grading method, which is based on blastocoel expansion, inner cell mass (ICM), and trophectoderm (TE) quality, was used to evaluate all Day 5 blastocysts morphologically. An artificial intelligence (AI)-based deep learning platform was used to further evaluate high-resolution embryo images in order to produce genetic competence and embryo viability ratings for evaluation of implantation potential and anticipated euploidy.

Conventional Morphological Assessment

On the fifth day of development, all embryos were subjected to a traditional morphological assessment using Gardner's blastocyst grading system by skilled embryologists. The following morphological characteristics were used to evaluate blastocysts:

- The extent of blastocoel expansion
- The quality of Inner Cell Mass (ICM),
- The morphology of the trophectoderm (TE).

Standard Gardner classification standards were used to classify the blastocysts. Higher-grade blastocysts, including 4AA, 4AB, and 3AA, were thought to have better morphology and a higher chance of implanting. Only Grade A blastocysts were used for additional genetic analysis and AI-based assessment.

AI-Based Embryo Assessment

A deep learning-based analytical tool for automated evaluation of Day 5 blastocyst morphology was used for AI-assisted embryo examination. The AI system examined high-resolution embryo photos taken during embryological assessment.

Several morphological characteristics were retrieved by the AI platform, including: • Blastocoel expansion properties,

- The morphology of Inner Cell Mass (ICM),
- The quality of trophectoderm (TE),
- The overall structural integrity of the blastocyst.

The AI system produced the following using morphological parameters derived from the image:

1. Implantation potential is predicted by embryo viability scores.
2. Genetic competence scores that calculate the likelihood of euploidy in embryos.

In addition to serving as a clinical decision-support tool, the AI system's predictive value in embryo selection during ART operations was retrospectively assessed.

Classification of embryos on the basis of two analytical pathways

Depending on the patient's request for genetic testing, eligible embryos were divided into two analytical pathways.

AI-Assisted Genetic Assessment Pathway

Patients who chose Pre-implantation Genetic Testing for Aneuploidy (PGT-A) received both PGT-A analysis and AI-assisted genetic evaluation. Trophectoderm biopsy and chromosomal analysis were performed on grade A blastocysts in order to identify euploidy and aneuploidy.

The congruence between projected embryo ploidy status and actual chromosomal outcomes was assessed by retrospectively comparing AI-generated genetic competence scores with verified PGT-A results.

Aneuploid embryos were not allowed to be transferred. During frozen embryo transfer cycles, euploid embryos were cryopreserved and then transferred. Serum β-hCG positive after embryo transfer was used to measure implantation success.

AI-Based Viability Assessment Pathway

Patients who did not choose genetic testing just had their embryo viability evaluated using AI. AI-derived viability grading was used to assess grade A blastocysts in order to forecast their probability for implantation. Vitrification techniques were used to cryopreserve certain embryos, which were then thawed for frozen embryo transfer cycles. After embryo transfer, serum β-hCG positivity was used to determine the implantation result. By comparing AI-predicted implantation potential with actual implantation results, the predictive usefulness of AI-derived viability scores was confirmed.

Cryopreservation and Frozen Embryo Transfer Protocol

In accordance with institutional laboratory regulations, all chosen blastocysts were cryopreserved using conventional vitrification techniques. Blastocysts were thawed and evaluated for post-thaw survival prior to embryo transfer.

Following the proper endometrial preparation procedures, frozen embryo transfer was carried out under ultrasound guidance. Standard clinical practice was followed when administering luteal phase support. To ascertain the outcome of implantation, serum β-hCG testing was carried out after embryo transfer.

Outcome Measures

Primary Outcome Measures

Implantation success—defined as positive serum β-hCG after frozen embryo transfer—was the main end measure.

Secondary Outcome Measures

Among the secondary outcome measures were:

- The relationship between implantation results and AI-derived embryo viability scores. • Blastocyst morphology grades and implantation success are related.
- Consistency between verified PGT-A results and AI-generated genetic competency scores.

- Comparative implantation results between embryos with different morphological grades and AI viability ratings.

Data Collection methods

Retrospective data collection from electronic medical records, embryology laboratory records, and institutional ART databases was used in this investigation.

The variables listed below were gathered and examined:

- Patient demographic characteristics,
- IVF treatment cycle details,
- Embryo morphology grades,
- AI-derived embryo viability scores,
- AI-derived genetic competence scores,
- PGT-A results,
- Frozen embryo transfer details,
- Serum β-hCG implantation outcomes.

All patient identifiers were removed prior to data analysis to maintain patient confidentiality and privacy.

Statistical Analysis

Using the proper statistical software, such as SPSS or R statistical software, statistical analysis was carried out.

Descriptive Statistics

Depending on the data distribution, continuous variables were reported as mean ± standard deviation (SD) or median with interquartile range (IQR). Frequencies and percentages were used to express categorical variables.

Comparative Analysis

The following methods were used to compare the β-hCG positive and β-hCG negative groups:

- Chi-square test,
- Fisher’s exact test,

for categorical variables as appropriate.

The following methods were used to examine continuous variables:

- For variables with a normal distribution, the student's t-test

- For non-parametric variables, use the Mann-Whitney U test.

Statistical significance was defined as a p-value of less than 0.05.

Correlation Analysis

Depending on the data distribution, Pearson or Spearman correlation coefficients were used to assess the relationship between AI-derived embryo viability scores and implantation outcomes.

Concordance Analysis

Concordance analysis and Cohen's kappa coefficient were used to evaluate the degree of agreement between AI-generated genetic competency scores and verified PGT-A results.

Receiver Operating Characteristic (ROC) Curve Analysis

The predictive performance of AI-derived embryo viability scores for implantation result prediction was assessed using Receiver Operating Characteristic (ROC) curve analysis. Sensitivity, specificity, and Area Under the Curve (AUC) values with matching 95% confidence intervals were calculated to evaluate the diagnostic utility of the AI model.

The effectiveness of AI-derived embryo viability scores to distinguish between embryos that resulted in positive and negative serum β-hCG outcomes after frozen embryo transfer was assessed using ROC analysis. For comparison analysis and predictive evaluation, a graphic depiction of ROC curves and implantation outcome trends across morphological grades and AI viability score categories was created.

Ethical Considerations

The Institutional Ethics Committee granted ethical permission for the study before retrospective data collection and analysis. Every technique was carried out in compliance with the principles and institutional ethical norms. Throughout the trial, patient privacy and confidentiality were rigorously upheld.

RESULTS

Study Population and Baseline Characteristics

During the study period, 345 frozen embryo transfer (FET) cycles were retrospectively examined. 340 cycles with conclusive serum β-hCG findings were included in the final study after cycles with partial implantation outcome data were excluded. Autologous Intra Cytoplasmic Sperm Injection (ICSI)-based IVF cycles using Day 5 blastocyst-stage embryos transferred during frozen embryo transfer cycles comprised all included cycles.

Of the 340 cycles that were examined, 237 had positive serum β-hCG values, and 103 had negative β-hCG results. The total implantation rate was 69.7%. Retrospective analysis was done on baseline

embryological features such as blastocyst morphology grades, AI-derived embryo viability ratings, and AI-assisted genetic competence scores.

Embryo Assessment Outcomes

Using Gardner's blastocyst grading method, which is based on blastocoel expansion, inner cell mass (ICM), and trophectoderm (TE) quality, all Day 5 blastocysts were evaluated morphologically. Additionally, a deep learning platform based on artificial intelligence (AI) was used to assess the embryos in order to generate scores for genetic competency and embryo-viability.

When compared to lower-grade embryos, higher-grade blastocysts showed better implantation results. According to Table 1, embryos with higher AI-derived viability scores also showed better β-hCG positive rates, indicating greater implantation potential.

Table 1
Parameters to show comparison of embryo viability scores

Parameter	Positive Mean	Negative Mean	p-value
Emb1	8.39	7.28	0.0004
Emb2	8.31	8.15	0.6309
Genetic	8.73	7.72	0.1534

Positive β-hCG outcomes were statistically significantly associated with Embryo 1's embryo viability score ($p < 0.001$). The genetic score and Embryo 2 viability score did not differ statistically significantly between the positive and negative groups.

Morphological Grade Analysis

Morphological grading was used to classify blastocysts, and implantation results were compared between various embryo grades. When compared to lower-grade embryos such as 3AB, 4BB, and other morphological grades shown in Fig. 2, blastocysts graded as 4AA, 4AB, and 3AA showed relatively greater implantation rates.

Table 2 below illustrates the substantial correlation between blastocyst morphology grade and implantation outcome ($p = 0.001$) found by statistical analysis using the Chi-square test, suggesting that better morphological traits were linked to better implantation success.

Table 2
Correlation Between Blastocyst Morphology Grade and β-hCG Outcome

Morphology Grade	β-hCG Positive (n)	β-hCG Negative (n)	Total (n)	Implantation Rate (%)
4AA	46	11	57	80.7
4AB	65	23	88	73.9
3AA	17	8	25	68.0
3AB	51	12	63	81.0
4BB	2	1	3	66.7
Others	56	48	104	53.8

The association between blastocyst morphology grade and implantation outcome was statistically significant (p = 0.001).

AI-Based Viability Score Analysis

AI-derived embryo viability scoring was used to retroactively assess embryos that were not subjected to genetic testing. For comparison implantation analysis, embryos were divided into low-, moderate-, and high-score groups based on AI-generated scores.

Twenty of the embryos in the low-score group had negative implantation results, and 23 had positive β-hCG outcomes. There were 40 β-hCG positive and 21 β-hCG negative results in the moderate-score group. With 155 β-hCG positive outcomes compared to 54 negative outcomes, the group with the highest AI viability score showed the highest implantation success.

As AI-derived viability scores increased, implantation success gradually increased. Table 3 makes it quite evident.

Table 3
Correlation between AI viability Score and β-hCG outcomes

AI Viability Score Category	β-hCG Positive (n)	β-hCG Negative (n)	Total (n)	Implantation Rate (%)
Low Score	23	20	43	53.5
Moderate Score	40	21	61	65.6
High Score	155	54	209	74.2

Statistical analysis revealed a significant association between AI viability score category and implantation outcome (p = 0.013).

ROC Curve Analysis of AI-Derived Embryo Viability Score

The predictive performance of AI-derived embryo viability scores for implantation result prediction was assessed using Receiver Operating Characteristic (ROC) curve analysis.

The ROC analysis showed that the AI model had a reasonable predictive accuracy for differentiating between embryos that produced positive and negative serum β-hCG results. The Area Under the Curve (AUC) showed that AI-assisted embryo viability evaluation performed satisfactorily in predicting implantation success.

Figure 3. illustrates the ROC curve analysis of AI-derived embryo viability scores for implantation outcome prediction.

ROC analysis demonstrated moderate predictive accuracy of AI-derived embryo viability scores for implantation outcome with an AUC of 0.91.

Concordance Analysis of AI Genetic Scoring and PGT-A

Pre-implantation Genetic Testing for Aneuploidy (PGT-A) and AI-assisted genetic grading were performed on grade A blastocysts from patients who chose genetic testing. The congruence between projected embryo ploidy status and actual chromosomal outcomes was assessed by retrospectively comparing AI-generated genetic competence scores with verified PGT-A results.

AI-assisted genetic prediction showed a moderate degree of agreement with verified PGT-A results. AI-based genetic prediction and verified chromosomal analysis showed fair agreement, with a kappa value of 0.257, according to agreement analysis using Cohen's kappa coefficient. Table 4 makes this very evident.

When compared to aneuploid embryos, euploid embryos found by PGT-A analysis showed somewhat better implantation results.

Table 4
Concordance between AI genetic score and PGT-A results

AI Genetic Prediction	Euploid (n)	Aneuploid (n)	Total (n)
Predicted Euploid	21	1	22
Predicted Aneuploid	3	1	4

Agreement analysis demonstrated fair concordance between AI-based genetic predictions and confirmed PGT-A results with a Cohen’s kappa coefficient of 0.257.

Implantation Outcome Analysis

Positive serum β-hCG levels after frozen embryo transfer were used to determine implantation success. Implantation results were consistently better for embryos with better morphological grades and higher AI-derived viability ratings, as seen in Table 5 and Fig. 4.

Embryos with superior blastocyst morphology grades and those classified in the high AI viability score category had higher implantation rates. Furthermore, compared to embryos predicted or confirmed as aneuploid, euploid embryos discovered by combining AI-assisted genetic scoring and PGT-A assessment showed better implantation potential.

Table 5
Overall Implantation Outcomes

Outcome	Number of Cases (n)	Percentage (%)
β-hCG Positive	237	69.7
β-hCG Negative	103	30.3
Total	340	100

Correlation and Statistical Analysis

Chi-square and Fisher's exact tests for categorical variables and Student's t-test or Mann-Whitney U test for continuous data, when applicable, were used in comparative statistical analysis.

Blastocyst morphology grade and implantation outcome were found to be statistically significantly correlated ($p = 0.001$). Similarly, there was a strong connection ($p = 0.013$) between implantation success and AI-derived embryo viability scores.

Implantation outcomes were positively correlated with rising AI-derived viability scores, according to correlation analysis. When compared to verified PGT-A results, concordance analysis provided additional evidence for the predictive value of AI-assisted genetic scoring.

Table 6
Comparative Statistical Analysis of Factors Associated with Implantation Outcomes

Variable	β-hCG Positive	β-hCG Negative	p-value
Embryo 1 Viability Score	8.39	7.28	0.0004
Embryo 2 Viability Score	8.31	8.15	0.6309
Genetic Score	8.73	7.72	0.1534
High AI Viability Score (%)	74.2	25.8	0.013
Superior Morphology Grade (%)	Higher	Lower	0.001

Table 6 summarizes comparative statistical findings between β-hCG positive and negative implantation outcome groups.

DISCUSSION

The therapeutic efficacy of Artificial Intelligence (AI)-assisted blastocyst assessment in predicting implantation outcomes during Assisted Reproductive Technology (ART) operations was assessed in the current retrospective observational cohort study. The study showed a strong correlation between implantation success after frozen embryo transfer (FET) cycles and both conventional blastocyst morphology assessment and AI-derived embryo viability score.

Analysis was done on 340 Day 5 blastocyst-stage frozen embryo transfer cycles. With 237 cycles showing positive serum β-hCG results, the overall implantation rate was 69.7%. The results of this study indicate that both AI-assisted embryo analysis and traditional embryo morphological grading could be useful methods for enhancing embryo selection during ART procedures.

In IVF labs, blastocyst morphology is still one of the most popular non-invasive techniques for choosing embryos. Embryos with better morphological grades had somewhat greater implantation rates in this study. When compared to lower-grade embryos and other morphology categories, blastocysts graded as 4AA, 4AB, and 3AB showed better β-hCG positive rates. Additionally, statistical analysis showed a substantial correlation ($p = 0.001$) between the grade of blastocyst morphology and the outcome of implantation. These results are in line with earlier research that found higher-grade blastocysts with superior Inner Cell Mass (ICM) and Trophectoderm (TE) morphology had better implantation and pregnancy outcomes.

The current study assessed AI-derived embryo viability grading as a prognostic tool for implantation success in addition to traditional morphological evaluation. When compared to embryos in the low- and moderate-scoring groups, those in the high AI viability score group showed better implantation results. Implantation rates increased steadily as AI-derived viability scores increased, and statistical analysis showed a substantial correlation between implantation outcome and AI viability score category ($p = 0.013$).

Receiver Operating Characteristic (ROC) curve analysis, which showed an acceptable discriminatory capacity of AI-derived embryo viability scores for predicting implantation success, further reinforced the predictive performance of AI-assisted embryo evaluation. These results imply that AI-based embryo evaluation could lessen the subjectivity of traditional morphological evaluation while offering an objective and repeatable method for embryo selection.

Additionally, the current study assessed the agreement between verified Pre-implantation Genetic Testing for Aneuploidy (PGT-A) results and AI-generated genetic competence scores. With a Cohen's kappa coefficient of 0.257, agreement study showed a fair degree of concordance between confirmed chromosomal findings and AI-assisted genetic prediction. When compared to aneuploid embryos, euploid embryos showed significantly better implantation outcomes, despite the moderate observed agreement. These results provide credence to the potential usefulness of AI-assisted embryo analysis as an additional non-invasive method for estimating the genetic competence of embryos.

The use of deep learning algorithms and artificial intelligence in reproductive medicine has drawn more attention, according to a number of recent research. It has been observed that AI-assisted embryo assessment systems reduce inter-observer variability among embryologists, increase consistency in embryo selection, and improve prediction of embryo implantation potential. The current study's results provide more proof that AI-assisted embryo evaluation can be used clinically in contemporary IVF procedures.

The current study has a number of advantages. A comparatively homogeneous cohort of autologous ICSI-based IVF cycles using Day 5 blastocysts transplanted during frozen embryo transfer cycles was included in the study. By excluding Day 6 blastocysts, cleavage-stage embryos, and fresh embryo transfers, biological variability was reduced and the consistency of implantation result evaluation was enhanced. Additionally, a thorough review of embryo selection techniques was produced by combining the evaluation of conventional morphology, AI-derived viability rating, and PGT-A concordance.

It is important to recognize some restrictions, though. The study's retrospective design restricts the causal interpretation of results and may create selection bias. The results may not be as applicable to larger populations because the study was carried out at a single ART center. Additionally, the level of concordance study between AI genetic prediction and validated chromosomal outcomes may have been impacted by the comparatively small number of embryos receiving PGT-A analysis.

Notwithstanding these drawbacks, the results of this study indicate that AI-aided embryo evaluation could be a useful supplementary tool for enhancing implantation results and optimizing embryo selection in assisted reproductive technology. To further evaluate the prognostic efficacy and clinical applicability of AI-assisted embryo assessment systems in reproductive medicine, higher sample numbers and standardized AI algorithms are needed in future prospective multicenter research.

The combined evaluation of conventional blastocyst morphology, AI-derived embryo viability assessment, and AI-assisted genetic competence prediction within a homogeneous cohort of Day 5 frozen embryo transfer cycles is a distinctive strength of the current study, offering a thorough and clinically relevant analysis of AI application in actual assisted reproductive technology practice.

Conclusion

The current study showed a strong correlation between implantation success in frozen embryo transfer cycles and both traditional blastocyst morphological assessment and AI-assisted embryo evaluation. Improved β-hCG positive rates were observed in higher-grade blastocysts and embryos with higher AI-derived viability scores. Additionally, AI-assisted embryo evaluation showed fair concordance with PGT-A results and acceptable predictive ability for implantation outcome prediction. These results provide credence to artificial intelligence's promise as a useful non-invasive decision-support tool for enhancing clinical outcomes and optimizing embryo selection in assisted reproductive technology.

Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ART	Assisted Reproductive Technology
AUC	Area Under the Curve
β-hCG	Beta Human Chorionic Gonadotropin
FET	Frozen Embryo Transfer
ICM	Inner Cell Mass
ICSI	Intracytoplasmic Sperm Injection
IVF	In Vitro Fertilization
IQR	Interquartile Range
PGT-A	Pre-implantation Genetic Testing for Aneuploidy
ROC	Receiver Operating Characteristic
SD	Standard Deviation
TE	Trophectoderm
WHO	World Health Organization

Declarations

Author Contribution

Dr. Esha Vatsa conceptualized and supervised the study. Anil Kumar conducted the literature review, data collection, analysis, and prepared the initial draft of the manuscript. Dr. Esha Vatsa reviewed, edited, and provided critical intellectual input throughout the study. Both authors contributed to the interpretation of the results, reviewed the manuscript, and approved the final version for publication.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available due to patient confidentiality and institutional data protection policies but are available from the corresponding author on reasonable request. All data were anonymized prior to analysis to protect patient privacy.

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Figures

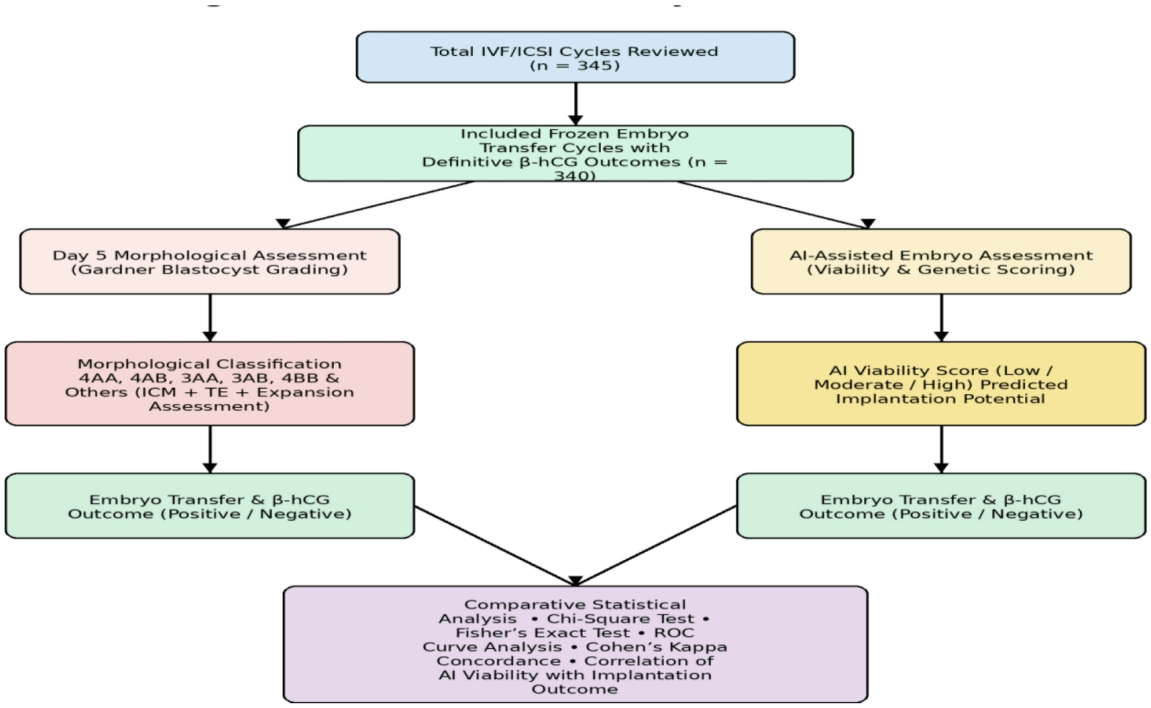


Figure 1

AI-Assisted blastocyst assessment workflow

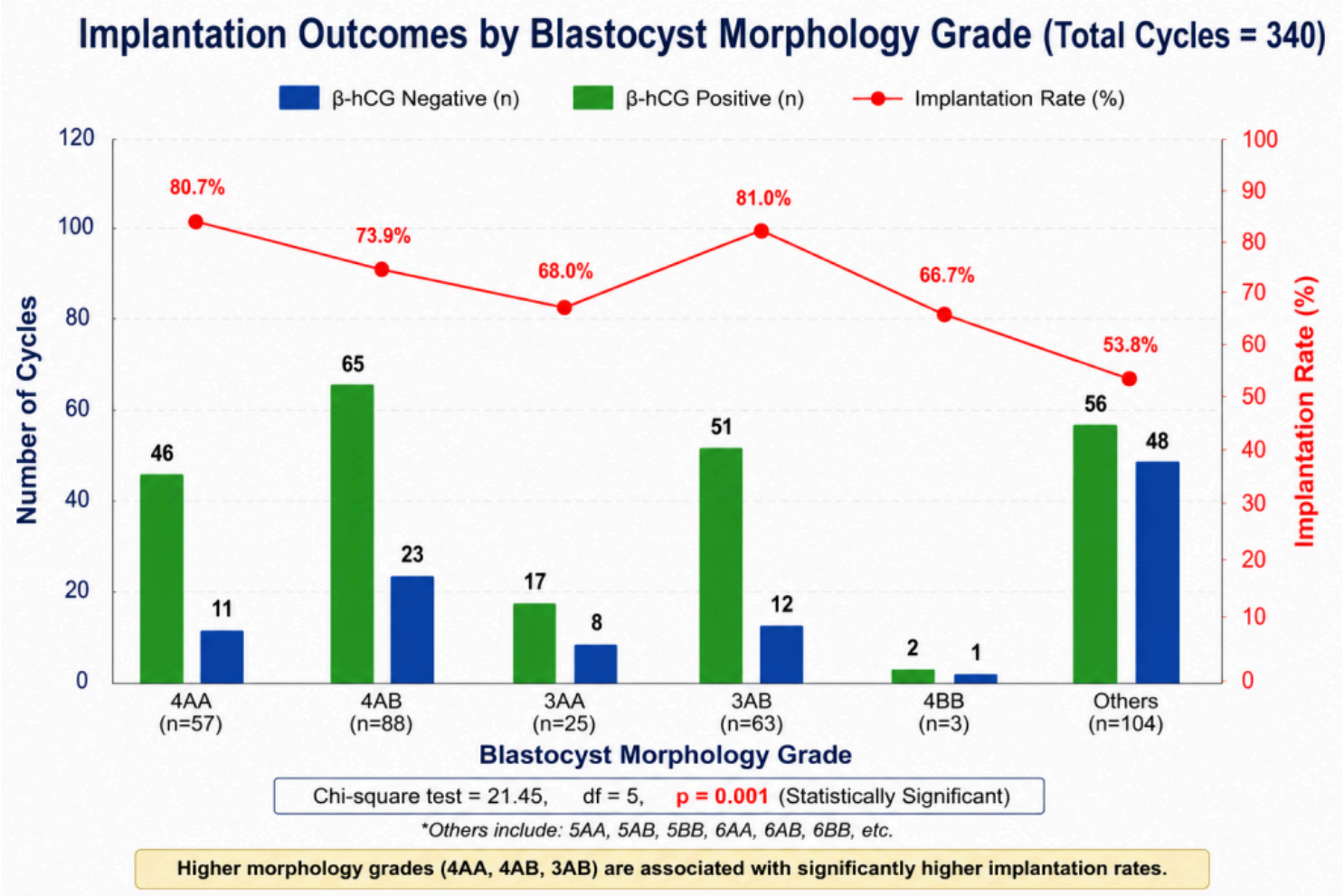


Figure 2

Implantation outcomes by blastocyst morphology grade

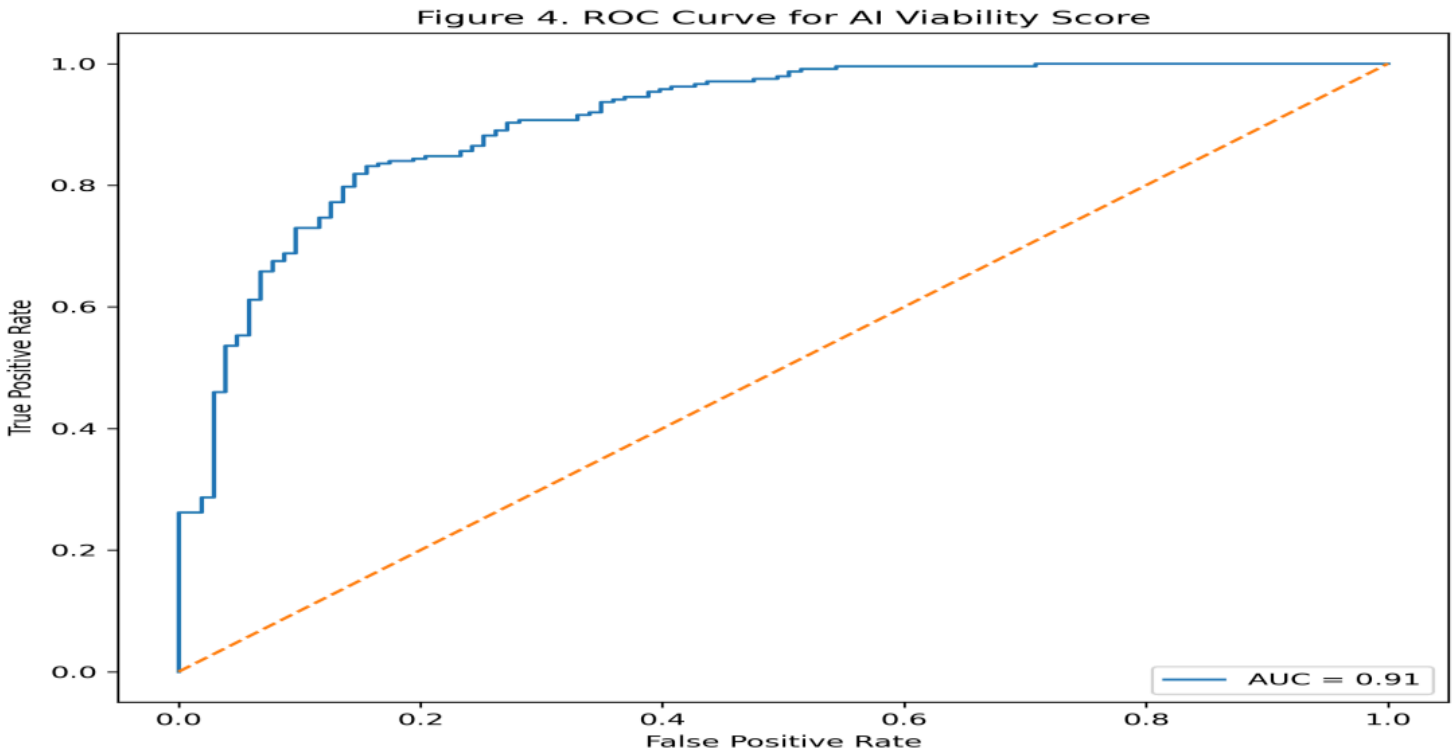


Figure 3

ROC Curve for AI Viability Score

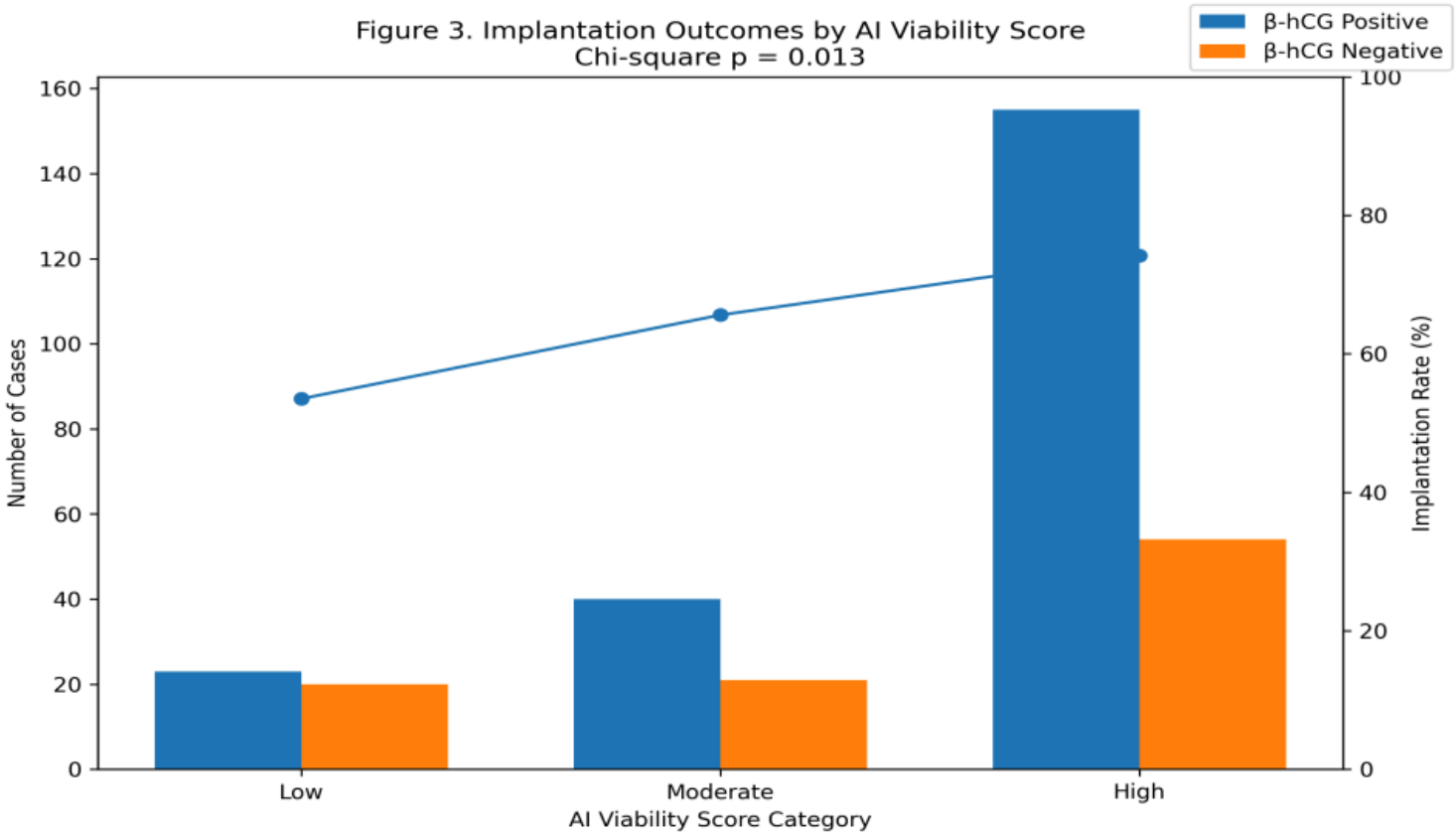


Figure 4

Implantation Outcomes by AI Viability Score