Review article

The Role of Artificial Intelligence from Preconception to Postpartum

Terezija Berlančić [1,2,3], Blaženka Miškić [4,5], Karla Miškić [4,6], Rajko Fureš [4,7], Ivana Erceg Ivkošić [4,8], Vesna Ćosić [4,9]

1 Faculty of Medicine Osijek, J. J Strossmayer University in Osijek, Croatia
2 Department of Gynecology and Obstetrics, General County Hospital Našice, Croatia
3 Faculty of Economics and Business in Osijek, J. J Strossmayer University, Osijek, Croatia
4 Faculty of Dental Medicine and Health Osijek, J. J Strossmayer University Osijek, Croatia
5 General Hospital "Dr. Josip Benčević" Slavonski Brod, Croatia
6 Dental Office dr. Karla Miškić, Slavonski Brod, Croatia
7 Department of Gynecology and Obstetrics, Zabok General Hospital and Croatian Veterans Hospital, Zabok, Croatia
8 St. Catherine Specialty Hospital, Zagreb, Croatia
9 Ćosić Polyclinic, Slavonski Brod, Croatia

*Corresponding author: Vesna Ćosić, vesna1.cosic@gmail.com

Abstract

Artificial intelligence (AI) is increasingly applied across obstetrics, supporting care from preconception to postpartum. By using large databases, including imaging, genomics, laboratory profiles, and electronic health records, machine learning and deep learning models can generate insights that surpass traditional methods, and enable more personalized maternal–fetal care. In the preconception and fertility stage, AI is a tool used in infertility diagnostics, sperm, oocyte and embryo selection in assisted reproductive technology, improving success rates and efficiency. During pregnancy predictive algorithms can help with monitoring fetal biometry and fetal growth rate. AI also contributes to intrapartum monitoring by providing more consistent interpretation of cardiotocography and contraction patterns, potentially reducing unnecessary interventions and improving neonatal outcomes. Similarly to ultrasound during pregnancy AI can be used to analyze intrapartum ultrasound monitoring and help in diagnosing dystocia which could lead to fewer cesarian sections and further complications. Intrapartum and during early postpartum period AI can be used to evaluate and predict possible postpartum hemorrhage. Despite significant progress, challenges remain regarding data quality, algorithmic bias, interpretability, and integration into everyday practice. However, with further research and use in everyday clinical practice AI has a possibility to become an irreplaceable tool to every practitioner.

Berlančić T, Miškić B, Miškić K, Fureš R, Erceg Ivkošić I, Ćosić V. The Role of Artificial Intelligence from Preconception to Postpartum. SEEMEDJ 2025; 9(S2); 110-120)

Received: Sep 25, 2025; revised version accepted: Dec 20, 2025; published: Dec 29, 2025

KEYWORDS: artificial intelligence, clinical decision support systems, machine learning, obstetrics and gynecology

Introduction

Artificial intelligence (AI) has become an emerging tool in modern medicine, changing the approach to research, diagnostics, decision making, prevention and therapy. Today AI has found its secure place in people's daily lives, and it can be found on recommendation systems, search engines, entities such as ChatGPT and facial recognition systems in smartphones, (OpenAITM, San Francisco, CA, USA) (1). AI has also been the point of discussion among many researchers, managers and professionals, working in the field of obstetrics and gynecology (OBGYN). AI can not only help solve the problem of misdiagnosis and missed diagnosis and provide health consulting services, but it can also promote the drug research speed and development as well as genetic testing and improve surgical accuracy and efficiency of pharmaceuticals (2,3). The opportunities to use and apply AI have increased exponentially with the ever-growing collection of big data, however with the more frequent application and usage the expectations of the AI users have also grown the interest in applying the AI in medical field has grown considerably, which can be seen by the large number of publications in the last couple of decades (4). Topic of AI in OBGYN has become so popular in recent years that the number of studies, relating to AI in different forms, increased four times from 2018-2023 compared to the previous period from 2012 to 2017 (5). All this has led to the increase of interest in AI as a tool to improve knowledge and provide better care in many OBGYN areas, one of them being conception and pregnancy.

Artificial intelligence: definition and short history

AI is defined as the simulation of human intelligence by a system or a machine, it's goal is is to develop a machine that can mimic human behaviors and think like humans which includes learning, perceiving, predicting, reasoning, planning and more (6). AI is used in various fields and technologies. It involves a series of learning methods, such as natural language processing, machine learning (ML), deep learning (DL), reinforcement learning and representation learning, heuristic analysis, etc (2). It is important to know that AI, ML and DL are not individual or separate but overlapping disciplines that are often put under one general umbrella term of AI in general population (7). ML is a subset of AI which puts focus on how computers learn with data, processing raw input data and recognizing patterns in them, analysing tem to enable predictions of output values so that it can it can identify trends and patterns which help it learn through past experiences creating the algorithm that is able to learn new tasks (1,8). DL, a subset of ML, is "organized in neural networks with multiple layers to perform more complex tasks, it uses convolutional neural networks, a class of deep neural networks developed to replicate the visual cortex' structure and organization" (1,8,9). Because they both have similarly organized neurons' connectivity pattern, convolutional neural networks are better at visual imaging analysis such as recognizing and detecting objects than other types of DL (1,10). Even though AI has become more popular in recent years it is not a completely new invention nor an idea. The birth of AI technology can be traced to 1950s and "Turing Test" which was a very simple question by Alan Turing in his paper titled "Computing Machinery and Intelligence", the question in regard was "Can machines think?" (6,11,12). This simple question started a revolution in AI development. One of the first practical implementations of AI and subsequentially ML was the robotic arm development in 1955 by General Motors which was just a primitive usage of AI by using it to mimic and emulate human actions (12). From then on AI grew exponentially and found its first usage in medicine. INTERNIST-1 was created in 1971 and was the world's first artificial medical consultant, it's utilization of a search algorithm to diagnose a patient based on their symptoms at the time represented a breakthrough in AI use in clinical research, showing it's potential to take some of the tasks of clinical diagnosis from healthcare providers and give them a mechanism to cross-check differential diagnoses (12,13). AI in medicine had shown promising applications and the National Institutes of Health sponsored the first AI in

Medicine conference which occurred at Rutgers University in 1970s (14). However, commercially-driven optimism following the premature generalization of AI, and the underestimate of the cost of maintaining, developing, ensuring reliable performance of expert knowledge-bases and keeping up-to-date, contributed to a so called "AI Winter" in the 1980's (14,15). The modern era of AI started in 2007 with "Watson", an IBMs creation of a question answering system, that could outcompete champions and top contestants on TV show Jeopardy, using language processing to extract information from different sources and analyzing them to arrive at an answer depending on contexts (12,16,17). Today, with improvement of computing power and the advent of big data technologies, deriving information and features from large data samples has become more efficient, leading to the proposal of an increasing number of novel training methods and neural network structures aimed at enhancing the representative learning ability of DL and expanding its and AI's general applications (6).

Artificial intelligence and Conception

The fast development of assisted reproductive technologies including oocyte and embryo cryopreservation, preimplantation genetic testing, assisted fertilization, and embryo selection technologies have improved the pregnancy rate since the birth of the first in vitro fertilization (IVF) baby, however problems remain, with most prominent ones being the quality of oocytes and sperm in general (18,19). Nelson et al. developed three validated prediction models using boosted tree modeling with antiMullerian hormone (AMH) or antral follicle count (AFC) to link cycle characteristics to live-birth probabilities. They used clinical cycle characteristics with either AMH, AFC, or both AMH and AFC to create three distinct predictor models to assess the prognostic impact of AMH and/or AFC on clinical pregnancy and were able to show that the AMH model alone had the highest predictor power, significantly improving model predictive performance over age alone by 76.2% (20,21). Another research used a random forest algorithm to predict clinical pregnancy which outperformed traditional logistic regression and even though random forest algorithm outperformed it just slightly it could rank predictors of clinical pregnancy, to assess for variable impact and importance on positive pregnancy outcomes (20,22). AI can also aid in optimizing the timing and dosage of medications used for ovarian stimulation, which reduces the likelihood of under stimulation or even more importantly overstimulation, which could result in improved patient outcomes and enable physitians to treat more patients with better efficiency and accuracy, driving increased financial and clinical value (20). AI has shown promising results in ART and the IVF laboratories by improving the efficiency and quality of IVF procedures especially in the development of methods of oocyte and sperm quality assessment (19,23). Semen parameters are a strong prognostic indicators of pregnancy and fertilization success and, in cases where semen parameters are not optimal, ART based techniques can help sperm to overcome the barriers of female reproductive tract (24,25). Although the technology has advanced greatly and there is a growing number of available techniques of sperm selection, the final sperm selection is still mostly performed by an embryologist manually based on the World Health Organization criteria and that assessment depends on the individual person, therefore the whole process is very staff specific and highly subjective with repercussions on ART success (25–27). Regarding the sperm morphology its assessment is performed by using different staining methods on a sperm sample and AI and ML algorithms have shown a potential in overcoming the mentioned problems (28). Deep neural network and support vector machines are 2 of the most commonly used algorithm structures (25). Studies showed that sperm morphology could be assessed with an accuracy of approximately 98% when used alone for both sperm concentration and morphology, or 88.5% when assessing sperm morphology in combination with deep learning algorithms (25,29,30). Sperm motility, another key parameter in standard semen analysis, is often evaluated using computer-assisted systems, and integrating video analysis with AI enables more accurate and rapid assessment of movement differences based on linear motion (23). Recent studies indicate that AI can match or surpass standard methods in motility classification, offering a faster and more cost-effective alternative to conventional semen analysis (23,31,32). Currently, few studies have applied convolutional neural networks and support vector machines to analyze oocyte images for predicting developmental potential, mainly focusing on identifying oocytes with higher potential through analysis of static morphological features(23). The performance of neural networks, like all ML algorithms, depends heavily on the quality of their training dataset, meaning that as larger and higher-quality data become available, these systems will achieve greater accuracy and robustness in the future. (25).

Ultrasound monitoring during pregnancy

Obtaining standard anatomical planes in ultrasound is one of the most critical yet challenging aspects of obstetric imaging, as it requires extensive training and clinical expertise and manual acquisition of these planes is subject to high intra-class variability and inter-class similarity, making interpretation challenging (33,34). AI development in obstetric ultrasound is still in its early stages due to challenges such as fetal movement, evolving fetal anatomy, and the difficulty of obtaining specific diagnostic planes limited by fetal position and maternal body habitus. (33). Additionally, inherent ultrasound issues such as acoustic shadows, speckle noise, motion blurring, and unclear boundaries further contribute to low detection rates (35). AI-based solutions, particularly convolutional neural networks, have demonstrated strong performance in recognizing standard planes without manual feature engineering (36). A research from 2018 used deep convolutional neural network to identify fetal facial standard planes, improving recognition accuracy and streamlining clinical workflows but the limited number of labeled training samples caused the deep convolutional neural network to overfit, resulting in reduced performance (37). Chen et al. employed transfer learning to adapt convolutional neural networks models pre-trained on large natural image datasets for identifying fetal abdominal standard planes, demonstrating high accuracy and robustness despite limited medical image datasets (38). Several deep learning models have been developed using various approaches for the automatic measurement of fetal biometry parameters, including biparietal diameter, occipitofrontal diameter, head circumference, and femur length (39). However, automatic measurement of fetal abdominal circumference is more difficult due to its unclear boundaries and irregular shape, leading researchers to propose using object detection or segmentation of key anatomical landmarks—such as te umbilical vein, stomach bubble, and fetal spine—before measuring the abdominal circumference. (39–41). Despite the progress, many AI studies in standard plane detection have been limited to datasets with predominantly normal fetuses, reducing applicability in pathological cases (34). Future directions involve developing larger, diversified, and pathology-inclusive datasets to strengthen the clinical utility of AI-based standard plane recognition (33).

Delivery and postpartum

Conventional predictive models, which depend largely on clinical expertise and traditional statistics, are limited by subjective biases and restricted variable sets, whereas artificial intelligence offers a more powerful alternative by analyzing large, high-dimensional datasets and uncovering complex relationships to enhance predictive accuracy (42). For medical personnel, childbirth is viewed as a sequence of procedures, assessments, and evaluations that guide the recommendation of the most appropriate delivery method, aiming to manage pregnancy-related complications and ensure the safety of both mother and child (43). Michalitsi et al. published a systematic review in 2024 where they found the most used input variables and outcomes. Common input variables included maternal age, gestational age, parity, gravity, labor induction type, cervical dilation, fetal weight, and other fetal and maternal health indicators, while outcome measures focused on mode of delivery, success or failure of vaginal birth after cesarean or labor induction, with some studies also incorporating intrapartum monitoring. (42). Today there are two most common types of intrapartum monitoring which are cardiotocogram (CTG) and intrapartum ultrasound. Today CTG is the most widely used method to monitor fetal condition during labor, but its clinical value is debated, as it has not reduced severe complications except neonatal seizures, while its use to detect fetal compromise has been linked to a significant rise in cesarean sections and instrumental vaginal deliveries (44,45). Computerized analysis of CTG signals significantly advances early detection and prediction of pathological outcomes, helping to reduce fetal morbidity and mortality and guide the need for surgical intervention. (46). Melaet et al. tested an AI algorithm that predicts future fetal heart rate based on prior subject-specific responses to uterine contractions, assuming a healthy fetus, where rapid deviations from expected responses result in poor fetal heart rate predictions, indicating a potentially compromised fetal state (44). The method showed strong agreement with expert annotations in distinguishing normal from pathological findings, indicating its potential to support clinicians in assessing fetal condition. (44). Another study employed a random forest model, a robust algorithm capable of capturing complex patterns, handling large datasets, and extracting meaningful features for accurate prediction. (47,48). Their results showed that, compared to other standard machine learning techniques like artificial neural networks, support vector machines, and recurrent neural networks, their model outperformed in prediction accuracy, robustness, and reliability (48). Intrapartum ultrasonography has proven highly useful in labor management over the past four decades, especially for dystocic labor, by improving diagnostic accuracy of fetal malpositions that are difficult to assess via conventional vaginal examination due to caput succedaneum and molding obscuring key landmarks (49–53). The Artificial Intelligence Dystocia Algorithm (AIDA) marks a major advancement in applying AI to intrapartum care and was developed through two key studies, AIDA 1 and AIDA 2 (54,55). AIDA integrates multiple geometric parameters from intrapartum ultrasonography with machine learning algorithms to assess labor progress and predict delivery outcomes (53). By simultaneously measuring four geometric parameters—the angle of progression, asynclitism degree, head–symphysis distance, and midline angle—AIDA provides a comprehensive, objective assessment of fetal position and the spatial relationship with the maternal pelvis, offering potential for evaluating various types of dystocia (53–55).

After the delivery there are many possible outcomes and complications to consider. Post-delivery, neural networks and decision tree models have been used to predict both the mode of delivery and complications, including postpartum hemorrhage and neonatal intensive care unit admissions (56). Postpartum hemorrhage (PPH) is a major, most serious childbirth complication and a leading cause of maternal mortality worldwide, and while prompt detection is crucial, diagnosis is challenging due to reliance on estimating blood loss (57). Liu et al. investigated methods to improve PPH prediction in vaginal deliveries, finding that a combined Light Gradient Boost and Logistic Regression model performed best, with key predictive factors including hematocrit, shock index, contraction frequency, white blood cell count, pregnancy-induced hypertension, newborn weight, second-stage labor duration, amniotic fluid index, and maternal body mass index (58). Akazawa et al. developed a deep learning model with two neural network layers following ensemble learning of five classifiers—logistic regression, support vector machine, random forest, XGBoost, and decision tree—using 11 variables from vaginal deliveries (including maternal age, parity, pre-pregnancy and admission weight, height, baby's sex, gestational age, birthweight, fetal position, delivery mode and oxytocin use,) to classify cases into non-PPH

(<1000 ml blood loss) and PPH (>1000 ml blood loss) groups (59). Even though the studies have shown AI and ML as good models to predict PPH with generally low to moderate risk of bias overall further research is needed on larger datasets to further explore the models since the use of AI and ML in medical decision making has legal and ethical implications(57).

Conclusion

The trend of advancement of AI, as well as ML and DL, and its implication in OBGYN clinical practice is one of the most interesting topics in modern medicine that still needs to be heavily researched. AI has undoubtedly entered an era of exponential growth, with rapid advancements in computational power, algorithmic design, and access to large-scale datasets being the main forces to push its further development and growth. In OBGYN and particularly in fetomaternal medicine, application of AI is demonstrating a significant promise in areas such as risk prediction, imaging interpretation, and real-time monitoring. However, despite the impressive progress seen in research settings, most developed models remain insufficiently validated and are rarely translated into routine clinical practice. A primary concern remains the issue of data quality since most of the research was done in high income countries. Secondly the studies are so far mostly experimental and are not used widely in everyday practice. Limitations include restricted generalizability across diverse populations, potential biases within training datasets, lack of transparency in decision-making, and challenges integrating AI tools into existing clinical workflows. Rather than being viewed as a replacement for clinician judgment, AI should be regarded as an adjunctive tool that can strengthen both research and patient care.

Acknowledgement. No acknowledgment.

Disclosure

Funding. No specific funding was received for this study.

Competing interests. None to declare.

References

1. Oliveira MBMD, Mendes F, Martins M, Cardoso P, Fonseca J, Mascarenhas T, et al. The Role of Artificial Intelligence in Urogynecology: Current Applications and Future Prospects. Diagnostics. 2025 Jan 24;15(3):274.

2. Peng Y, Liu E, Peng S, Chen Q, Li D, Lian D. Using artificial intelligence technology to fight COVID-19: a review. Artif Intell Rev. 2022 Aug;55(6):4941–77.

3. Manickam P, Mariappan SA, Murugesan SM, Hansda S, Kaushik A, Shinde R, et al. Artificial Intelligence (AI) and Internet of Medical Things (IoMT) Assisted Biomedical Systems for Intelligent Healthcare. Biosensors. 2022 Jul 25;12(8):562.

4. Fischer A, Rietveld A, Teunissen P, Hoogendoorn M, Bakker P. What is the future of artificial intelligence in obstetrics? A qualitative study among healthcare professionals. BMJ Open. 2023 Oct;13(10):e076017.

5. Pinheiro YT, Silva RARD. Artificial intelligence in gynecology and obstetrics: from the enthusiasm of use in practice to the challenges of implementation. Rev Bras Ginecol E Obstetrícia. 2024 Jun 3;46:e-rbgo41.

6. Xu Y, Liu X, Cao X, Huang C, Liu E, Qian S, et al. Artificial intelligence: A powerful paradigm for scientific research. Innov Camb Mass. 2021 Nov 28;2(4):100179.

7. Le Berre C, Sandborn WJ, Aridhi S, Devignes MD, Fournier L, Smaïl-Tabbone M, et al. Application of Artificial Intelligence to Gastroenterology and Hepatology. Gastroenterology. 2020 Jan;158(1):76-94.e2.

8. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015 May 28;521(7553):436–44.

9. Chassagnon G, Vakalopolou M, Paragios N, Revel MP. Deep learning: definition and perspectives for thoracic imaging. Eur Radiol. 2020 Apr;30(4):2021–30.

10. Okagawa Y, Abe S, Yamada M, Oda I, Saito Y. Artificial Intelligence in Endoscopy. Dig Dis Sci. 2022 May;67(5):1553–72.

11. Turing A. Computing Machinery and Intelligence (1950). In: Copeland BJ, editor. The Essential Turing [Internet]. Oxford University PressOxford; 2004 [cited 2025 Aug 25]. p. 433–64. Available from: https://academic.oup.com/book/42030/chapter/355746326

12. Hirani R, Noruzi K, Khuram H, Hussaini AS, Aifuwa EI, Ely KE, et al. Artificial Intelligence and Healthcare: A Journey through History, Present Innovations, and Future Possibilities. Life Basel Switz. 2024 Apr 26;14(5):557.

13. Miller RA, Pople HE, Myers JD. Internist-I , an Experimental Computer-Based Diagnostic Consultant for General Internal Medicine. N Engl J Med. 1982 Aug 19;307(8):468–76.

14. Kulikowski CA. Beginnings of Artificial Intelligence in Medicine (AIM): Computational Artifice Assisting Scientific Inquiry and Clinical Art – with Reflections on Present AIM Challenges. Yearb Med Inform. 2019 Aug;28(01):249–56.

15. London AJ. Groundhog Day for Medical Artificial Intelligence. Hastings Cent Rep [Internet]. 2018 May [cited 2025 Aug 25];48(3). Available from: https://onlinelibrary.wiley.com/doi/10.1002/hast.842

16. Mintz Y, Brodie R. Introduction to artificial intelligence in medicine. Minim Invasive Ther Allied Technol. 2019 Mar 4;28(2):73–81.

17. Ferrucci D, Levas A, Bagchi S, Gondek D, Mueller ET. Watson: Beyond Jeopardy! Artif Intell. 2013 Jun;199–200:93–105.

18. Niederberger C, Pellicer A, Cohen J, Gardner DK, Palermo GD, O'Neill CL, et al. Forty years of IVF. Fertil Steril. 2018 Jul;110(2):185-324.e5.

19. Wang R, Pan W, Jin L, Li Y, Geng Y, Gao C, et al. Artificial intelligence in reproductive medicine. Reproduction. 2019 Oct;158(4):R139–54.

20. Hariton E, Pavlovic Z, Fanton M, Jiang VS. Applications of artificial intelligence in ovarian stimulation: a tool for improving efficiency and outcomes. Fertil Steril. 2023 Jul;120(1):8–16.

21. Nelson SM, Fleming R, Gaudoin M, Choi B, Santo-Domingo K, Yao M. Antimüllerian hormone levels and antral follicle count as prognostic indicators in a personalized prediction model of live birth. Fertil Steril. 2015 Aug;104(2):325–32.

22. Wang CW, Kuo CY, Chen CH, Hsieh YH, Su ECY. Predicting clinical pregnancy using clinical features and machine learning algorithms in in vitro fertilization. Viganò P, editor. PLOS ONE. 2022 Jun 8;17(6):e0267554.

23. Jiang VS, Bormann CL. Artificial intelligence in the in vitro fertilization laboratory: a review of advancements over the last decade. Fertil Steril. 2023 Jul;120(1):17–23.

24. Donnelly ET, Lewis SEM, McNally JA, Thompson W. In vitro fertilization and pregnancy rates: the influence of sperm motility and morphology on IVF outcome. Fertil Steril. 1998 Aug;70(2):305–14.

25. Cherouveim P, Velmahos C, Bormann CL. Artificial intelligence for sperm selection—a systematic review. Fertil Steril. 2023 Jul;120(1):24–31.

26. Barroso G, Mercan R, Ozgur K, Morshedi M, Kolm P, Coetzee K, et al. Intra- and inter-laboratory variability in the assessment of sperm morphology by strict criteria: impact of semen preparation, staining techniques and manual versus computerized analysis. Hum Reprod. 1999 Aug;14(8):2036–40.

27. Björndahl L, Kirkman Brown J. The sixth edition of the WHO Laboratory Manual for the Examination and Processing of Human Semen: ensuring quality and standardization in basic examination of human ejaculates. Fertil Steril. 2022 Feb;117(2):246–51.

28. Bijar A, Benavent AP, Mikaeili M, Khayati R. Fully automatic identification and discrimination of sperm's parts in microscopic images of stained human semen smear. J Biomed Sci Eng. 2012;05(07):384–95.

29. Kanakasabapathy MK, Sadasivam M, Singh A, Preston C, Thirumalaraju P, Venkataraman M, et al. An automated smartphone-based diagnostic assay for point-of-care semen analysis. Sci Transl Med. 2017 Mar 22;9(382):eaai7863.

30. Thirumalaraju P, Kanakasabapathy MK, Bormann CL, Kandula H, Sai Pavan SK, Yarravarapu D, et al. Human sperm morphology analysis using smartphone microscopy and deep learning. Fertil Steril. 2019 Sep;112(3):e41.

31. Ottl S, Amiriparian S, Gerczuk M, Schuller BW. motilitAI: A machine learning framework for automatic prediction of human sperm motility. iScience. 2022 Aug;25(8):104644.

32. Tsai VF, Zhuang B, Pong YH, Hsieh JT, Chang HC. Web- and Artificial Intelligence–Based Image Recognition For Sperm Motility Analysis: Verification Study. JMIR Med Inform. 2020 Nov 19;8(11):e20031.

33. Horgan R, Nehme L, Abuhamad A. Artificial intelligence in obstetric ultrasound: A scoping review. Prenat Diagn. 2023 Aug;43(9):1176–219.

34. Xiao S, Zhang J, Zhu Y, Zhang Z, Cao H, Xie M, et al. Application and Progress of Artificial Intelligence in Fetal Ultrasound. J Clin Med. 2023 May 5;12(9):3298.

35. Meng L, Zhao D, Yang Z, Wang B. Automatic display of fetal brain planes and automatic measurements of fetal brain parameters by transabdominal three-dimensional ultrasound. J Clin Ultrasound. 2020 Feb;48(2):82–8.

36. Drukker L, Noble JA, Papageorghiou AT. Introduction to artificial intelligence in ultrasound imaging in obstetrics and gynecology. Ultrasound Obstet Gynecol. 2020 Oct;56(4):498–505.

37. Yu Z, Tan EL, Ni D, Qin J, Chen S, Li S, et al. A Deep Convolutional Neural Network-Based Framework for Automatic Fetal Facial Standard Plane Recognition. IEEE J Biomed Health Inform. 2018 May;22(3):874–85.

38. Chen H, Ni D, Qin J, Li S, Yang X, Wang T, et al. Standard Plane Localization in Fetal Ultrasound via Domain Transferred Deep Neural Networks. IEEE J Biomed Health Inform. 2015 Sep;19(5):1627–36.

39. Ramirez Zegarra R, Ghi T. Use of artificial intelligence and deep learning in fetal ultrasound imaging. Ultrasound Obstet Gynecol. 2023 Aug;62(2):185–94.

40. Jang J, Park Y, Kim B, Lee SM, Kwon JY, Seo JK. Automatic Estimation of Fetal Abdominal Circumference From Ultrasound Images. IEEE J Biomed Health Inform. 2018 Sep;22(5):1512–20.

41. Kim B, Kim KC, Park Y, Kwon JY, Jang J, Seo JK. Machine-learning-based automatic identification of fetal abdominal circumference from ultrasound images. Physiol Meas. 2018 Oct 22;39(10):105007.

42. Michalitsi K, Metallinou D, Diamanti A, Georgakopoulou VE, Kagkouras I, Tsoukala E, et al. Artificial Intelligence in Predicting the Mode of Delivery: A Systematic Review. Cureus [Internet]. 2024 Sep 10 [cited 2025 Aug 26]; Available from: https://www.cureus.com/articles/291237-artificial-intelligence-in-predicting-the-mode-of-delivery-a-systematic-review

43. Owusu-Adjei M, Ben Hayfron-Acquah J, Frimpong T, Gaddafi AS. An AI-based approach to predict delivery outcome based on measurable factors of pregnant mothers. Villanueva C, editor. PLOS Digit Health. 2025 Feb 5;4(2):e0000543.

44. Melaet R, De Vries IR, Kok RD, Guid Oei S, Huijben IAM, Van Sloun RJG, et al. Artificial intelligence based cardiotocogram assessment during labor. Eur J Obstet Gynecol Reprod Biol. 2024 Apr;295:75–85.

45. Alfirevic Z, Keeney E, Dowswell T, Welton NJ, Medley N, Dias S, et al. Methods to induce labour: a systematic review, network meta-analysis and cost-effectiveness analysis. BJOG Int J Obstet Gynaecol. 2016 Aug;123(9):1462–70.

46. Xie W, Cai P, Hu Y, Lu Y, Chen C, Cai Z, et al. AI-driven paradigm shift in computerized cardiotocography analysis: A systematic review and promising directions. Neurocomputing. 2024 Nov;607:128446.

47. Jaba Deva Krupa A, Dhanalakshmi S, R K. An improved parallel sub-filter adaptive noise canceler for the extraction of fetal ECG. Biomed Eng Biomed Tech. 2021 Oct 26;66(5):503–14.

48. Moutaib M, Fattah M, Farhaoui Y, Aghoutane B, El Bekkali M. Fetal electrocardiogram prediction using machine learning: a random forest-based approach. Indones J Electr Eng Comput Sci. 2024 Feb 1;33(2):1076.

49. Caughey AB, Cahill AG, Guise JM, Rouse DJ. Safe prevention of the primary cesarean delivery. Am J Obstet Gynecol. 2014 Mar;210(3):179–93.

50. Chan VYT, Lau WL. Intrapartum ultrasound and the choice between assisted vaginal and cesarean delivery. Am J Obstet Gynecol MFM. 2021 Nov;3(6):100439.

51. Pergialiotis V, Bellos I, Antsaklis A, Papapanagiotou A, Loutradis D, Daskalakis G. Maternal and neonatal outcomes following a prolonged second stage of labor: A meta-analysis of observational studies. Eur J Obstet Gynecol Reprod Biol. 2020 Sep;252:62–9.

52. Malvasi A, Barbera A, Di Vagno G, Gimovsky A, Berghella V, Ghi T, et al. Asynclitism: a literature review of an often forgotten clinical condition. J Matern Fetal Neonatal Med. 2015 Nov 2;28(16):1890–4.

53. Malvasi A, Malgieri LE, Stark M, Tinelli A. Dystocia, Delivery, and Artificial Intelligence in Labor Management: Perspectives and Future Directions. J Clin Med. 2024 Oct 25;13(21):6410.

54. Malvasi A, Malgieri LE, Cicinelli E, Vimercati A, D'Amato A, Dellino M, et al. Artificial Intelligence, Intrapartum Ultrasound and Dystocic Delivery: AIDA (Artificial Intelligence Dystocia Algorithm), a Promising Helping Decision Support System. J Imaging. 2024 Apr 29;10(5):107.

55. Malvasi A, Malgieri LE, Cicinelli E, Vimercati A, Achiron R, Sparić R, et al. AIDA (Artificial Intelligence Dystocia Algorithm) in Prolonged Dystocic Labor: Focus on Asynclitism Degree. J Imaging. 2024 Aug 9;10(8):194.

56. Nwokoro CO, Uzoka FM, Inyang UG, Eyoh IJ, Duke OA, Nwokoro KCynthia, et al. Predicting Maternal Outcomes Using Tree-based Methods in Machine Learning [Internet]. 2024 [cited 2025 Aug 26]. Available from: https://www.researchsquare.com/article/rs-4359080/v1

57. Ranjbar A, Rezaei Ghamsari S, Boujarzadeh B, Mehrnoush V, Darsareh F. Predicting risk of postpartum hemorrhage using machine learning approach: A systematic review. Gynecol Obstet Clin Med. 2023 Sep;3(3):170–4.

58. Liu Y, Guo F, Zhou Y, Yang X, Zhang Y, Fan J. The Interactive Effect of Prepregnancy Overweight/Obesity and Isolated Maternal Hypothyroxinemia on Macrosomia. J Clin Endocrinol Metab. 2021 Jun 16;106(7):e2639–46.

59. Akazawa M, Hashimoto K, Katsuhiko N, Kaname Y. Machine learning approach for the prediction of postpartum hemorrhage in vaginal birth. Sci Rep. 2021 Nov 19;11(1):22620..

Author contribution.

Acquisition of data: TB, BM, KM, RF, IEI, VĆ
Administrative, technical, or logistic support: TB, BM, KM, RF, IEI, VĆ
Analysis and interpretation of the data: TB, BM, KM, RF, IEI, VĆ
Conception and design: TB, BM, KM, RF, IEI, VĆ
Critical revision of the article for important intellectual content: TB, BM, KM, RF, IEI, VĆ
Drafting of the article: TB, BM, KM, RF, IEI, VĆ
Final approval of the article: TB, BM, KM, RF, IEI, VĆ
Guarantor of the study: TB, BM, KM, RF, IEI, VĆ

Uloga umjetne inteligencije od prije začeća do postpartalnoga razdoblja

Sažetak

Umjetna inteligencija (UI) sve se više upotrebljava u opstetriciji, kao podržavajuća skrb od razdoblja prije začeća do postapartalnoga razdoblja. Korištenjem velikih baza podataka, uključujući slikovne pretrage, genomiku, laboratorijske profile i digitalne zdravstvene kartone, modeli strojnog učenja i dubokog učenja mogu proizvesti uvide koji nadilaze tradicionalne metode, i omogućuju višu razinu personaliziranosti za majku i plod. U razdoblju prije začeća i fertiliteta, UI se koristi u dijagnostici neplodnosti, selekciji spermija, jajnih stanica i embrija u potpomognutoj oplodnji, poboljšavajući izglede za uspjeh i učinkovitost. Tijekom trudnoće prediktivni algoritmi mogu pomoći u nadziranju biometrije fetusa i njegova razvoja. UI također pridonosi nadziranju tijekom poroda nudeći konzistentnije interpretacije kardiotokografije i uzoraka trudova, potencijalno umanjujući nepotrebne intervencije i poboljšavajući neonatalne ishode. Slično ultrazvuku tijekom trudnoće UI se može koristiti kako bi se analizirao ultrazvuk tijekom poroda i tko pomoći u dijagnosticiranju distocije što može rezultirati smanjenjem broja carskih rezova i daljnjih komplikacija. Tijekom poroda i ranog postpartalnog razdoblja UI može pomoći u procjeni i predviđanju mogućega postpartalnog krvarenja. Unatoč značajnom napretku, i dalje su prisutni izazovi u vezi s kvalitetom podataka, sustavnim pogreškama algoritama, interpretativnosti, i integraciji u svakodnevnu praksu. Međutim, uz daljnje istraživanje i upotrebu u kliničkoj svakodnevici, UI ima mogućnost postati nezamjenjiv alat svakoga praktičara.

Ključne riječi: umjetna inteligencija, sustavi za pomoć u kliničkom odlučivanju, cstrojno učenje, opstetricija i ginekologija