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SPECIAL FOCUS PAPER

Artificial Intelligence for Risk Stratification in Uterine Scar Pregnancy: A Review of Predictive Models and Clinical Decision Support Systems

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ABSTRACT

Uterine scar pregnancy is one of the emerging obstetric complications these days, most commonly in the form of cesarean scar pregnancy (CSP), which is linked to uterine rupture, uterine bleeding, hysterectomy, and placenta accreta spectrum (PAS). However, early risk stratification is challenging due to the nonspecific nature of symptoms and the operator dependence of ultrasound interpretation and clinical presentation that varies considerably. This structured narrative review explores the potential of artificial intelligence (AI), machine learning (ML), deep learning, and clinical decision support systems (CDSS) to enhance CSP risk assessment. The review aimed to identify and summarize the clinical and imaging factors associated with CSP risk, evaluate the reported performance of predictive models, assess multimodal, explainable, and workflow-integrated CDSS approaches, and identify barriers to clinical translation. The objectives were evaluated based on predefined evidence-extraction indicators. Among the selected ML models, those with strong discrimination were defined by the combination of heterogeneous endpoints, small cohorts, or cohorts limited to a single center, as well as limited external validation.

KEYWORDS

artificial intelligence (AI), machine learning (ML), cesarean scar pregnancy (CSP), clinical decision support systems (CDSS), risk stratification, predictive modelling, explainable AI

1 INTRODUCTION

Cesarean scar pregnancy (CSP) is an ectopic pregnancy where the gestational sac becomes implanted in the myometrial defect of a previous cesarean scar. It was first described formally as a distinct clinical entity in the early literature, and it has become a more important problem with the increasing rate of cesarean delivery (CD)

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worldwide [1–2]. CSP occurs in around 1 in 1,800–2,216 pregnancies in women with a previous CD and is a significant fraction of ePGs in this group of women [2].

In many cases, CSP can continue to develop beyond the first trimester without affecting the overall risk of complications for the mother. Complications associated with these events are uterine rupture, significant bleeding, emergency hysterectomy, and death [3, 4]. CSP is also associated with the placenta accreta spectrum (PAS), which adds to the complexity of surgery and morbidity of the mother [5]. Therefore, to counsel, select treatment, preserve fertility, and plan for referrals safely, early and reliable risk stratification is key.

The primary method of diagnosis is currently transvaginal ultrasonography (TVUS), which is supplemented, if required, with Doppler assessment, magnetic resonance imaging (MRI), sequential serum beta-human chorionic gonadotropin (β-hCG) levels, and clinical history. But ultrasound is operator dependent, CSP can mimic cervical pregnancy or miscarriage, and hormonal pattern alone is not considered to be specific enough [6]. However, artificial intelligence (AI) and machine learning (ML) could overcome these limitations by combining clinical, imaging, biochemical, and temporal data to make reproducible predictions for each patient [7].

1.1 Research question

How can AI-driven predictive models and clinical decision support systems (CDSS) improve risk estimation and clinical decision-making in uterine scar pregnancy, particularly CSP?

1.2 Research objectives (RO)

RO1: To synthesize the clinical, pathophysiological, biochemical, and imaging factors associated with CSP diagnosis and prognosis.

RO2: To evaluate the reported predictive performance of AI and ML models relevant to ectopic pregnancy, CSP prognosis, scar integrity, and related obstetric complications.

RO3: To assess the contribution of multimodal data fusion, explainable AI, EHR integration, and CDSS design to clinically useful risk stratification.

RO4: To identify limitations in validation, data quality, fairness, regulation, and real-world implementation and to propose priorities for future research.

The remainder of this paper is organized into a literature review, research methodology, results, discussion, and conclusion. This structure separates the existing evidence from the authors' synthesis and interpretation.

2 LITERATURE REVIEW

2.1 Clinical background, presentation, and pathophysiology

AI-enhanced clinical decision support in obstetric care: A CDSS uses patient-specific information to generate assessments, alerts, predictions, or recommendations that support clinical decision-making. AI-enhanced CDSS applications now span prenatal, intrapartum, and postpartum care and include diagnostic support, risk prediction, treatment recommendations, and knowledge-based guidance [12]. A related review of pregnancy-care CDSS research further demonstrates the breadth

of proposed applications, although many systems remain at the prototype or retrospective-validation stage [13].

EHR-based ML has been investigated for predicting postpartum hemorrhage, PAS, preeclampsia, and other maternal complications. These systems can combine obstetric history, laboratory measurements, vital signs, and longitudinal clinical records and may eventually incorporate genetic and multiomics data [14]. However, external validation, bias, regulation, and workflow integration remain major implementation challenges [15].

The Intelligent Scan Assistant System illustrates the potential value of CDSS in early pregnancy. In a controlled evaluation involving non-expert trainees, the system improved correct pregnancy-location diagnosis by 20% and accurate ectopic-pregnancy diagnosis by 30%, while also improving image quality and clinician confidence [16]. This finding is especially relevant to settings where expert sonographers are not consistently available.

2.2 Machine-learning approaches to obstetric risk prediction

Common supervised-learning methods in maternal and fetal health include logistic regression, support vector machines, decision trees, random forests, gradient-boosting algorithms such as XGBoost and CatBoost, and artificial neural networks [17]. Reviews of AI in pregnancy report broad use in prenatal diagnosis, preterm birth, gestational diabetes mellitus, preeclampsia, fetal growth disorders, and adverse perinatal outcomes [18–19].

Nonlinear and ensemble models are well suited to obstetric data because interactions among demographic, biochemical, temporal, and imaging variables are rarely linear. Gradient boosting performs particularly well with structured clinical data, whereas recurrent neural networks can model longitudinal EHR or biomarker trajectories [17]. One prospective study reported 92% accuracy and an AUC-ROC of 0.94 for an AI model predicting multiple obstetric risks, illustrating the broader potential of predictive analytics in maternal health [20]. General healthcare reviews likewise support the increasing use of ML for clinical prediction and pathology detection, while emphasizing the importance of validation and transparent reporting [21–22].

2.3 AI for ectopic pregnancy and CSP risk assessment

Pregnancy of unknown location (PUL) is a clinically important precursor state because a proportion of these pregnancies are ultimately diagnosed as ectopic. Reported ectopic-pregnancy rates among PUL cases are substantially higher than in the general reproductive population [23]. Traditional M4 and M6 models depend on serial progesterone and β-hCG measurements and may require follow-up over several days, which can delay decisions in high-risk cases [24].

A personalized ML model was developed using 1,896 patients with PUL compared to logistic regression, XGBoost, random forest, support vector machine, and CatBoost. CatBoost achieved an AUROC of 0.930 and an AUPRC of 0.685, with 76.2% sensitivity and 96.6% specificity using baseline data from the first visit [24]. Important predictors included vaginal bleeding, progesterone, an adnexal mass, gravidity, β-hCG, previous CD, previous pelvic surgery, and abdominal tenderness. SHAP analysis identified vaginal bleeding, progesterone, and adnexal mass as the strongest contributors, and the model was implemented as a web-based triage tool [24].

A CSP-specific prognostic classification system combined ML with a conventional linear score to balance predictive performance and clinical interpretability. Important morphometric predictors included the distance between the gestational sac and uterine cavity lining, implantation-plane thickness, RMT, and gestational-sac diameter at the scar niche [25]. These objective measurements may support individualized treatment planning more effectively than broad visual categories alone.

Another study used XGBoost to predict intraoperative uterine scar tenderness in 353 women undergoing repeat CD. The model achieved 86.4% accuracy, a macro-averaged F1-score of 0.83, and class-specific AUCs of 0.93, 0.87, and 0.91 [26]. SHAP highlighted the number of previous cesarean deliveries, a short inter-delivery interval, emergency delivery, high body mass index, and placenta previa as influential predictors. Although the endpoint was not CSP itself, the study demonstrates the feasibility of explainable scar-related risk prediction in routine obstetric care.

2.4 Conventional diagnostic modalities and classification systems

TVUS is the first-line imaging modality. Typical features seen in diagnosis include the presence of an anteriorly located gestational sac or trophoblastic mass at the previous lower uterine segment scar, absence of uterine cavity and cervical canal, thin or absent myometrial wall between the pregnancy and bladder, and a prominent peritrophoblastic vascularity on Doppler imaging [2]. Structured assessment of the scars, in conjunction with standardized acquisition in the sagittal and transverse planes, can decrease the level of diagnostic variability [8].

MRI can be helpful when ultrasound results are ambiguous or when the depth of invasion and/or bladder involvement need to be determined for surgical planning [9]. MRI also offers high soft-tissue contrast and can aid the objective assessment of PAS in high-risk patients [10].

Several classification systems describe CSP according to implantation location, growth direction, and the relationship between the gestational sac, uterine cavity, scar niche, and serosal surface. Endogenic or on-the-scar implantation generally has a more favorable prognosis than exogenic or in-the-niche implantation, which is associated with thinner intervening myometrium and a greater risk of rupture or PAS [2]. A combined clinical and ultrasound scoring system using β-hCG concordance, vaginal bleeding, gestational-sac morphology, Doppler findings, and fetal cardiac activity reported 95.6% sensitivity and 91.7% specificity at a threshold score of four [11]. Nevertheless, the absence of a universally adopted classification system and persistent inter-observer variation limit consistent use [6].

2.5 AI-enhanced clinical decision support in obstetric care

In a CDSS, the patient-specific information is used to produce assessments, alerts, predictions, or recommendations that support clinical decisions. The applications of AI have now reached the prenatal, intrapartum, and postpartum stages of the entire care continuum, encompassing diagnostics, risk prediction, treatment advice, and knowledge-based guidance [12]. A review of studies on pregnancy-care CDSS also shows the wide range of proposed applications, with most systems in the prototype or retrospective validation phase [13].

Several maternal complications, including PPH, PAS, and preeclampsia, have been studied using EHR-based ML. These systems may bring together

obstetric history, laboratory measurements, vital signs, and longitudinal clinical records and may eventually include genetic and multiomics-based data as a part of the record [14]. However, external validation, bias, regulation, and workflow integration are significant challenges to implementation [15].

The Intelligent Scan Assistant System (IAAS) demonstrates the potential benefit of CDSS in early pregnancy. The system increased the rate of correct pregnancy-location diagnosis by 20% and accurate ectopic-pregnancy diagnosis by 30% in an evaluation with non-expert trainees and confirmed image quality and the confidence of clinicians [16]. This discovery is particularly important in environments where skilled sonographers are not always on hand.

2.6 Machine-learning methods for obstetric risk prediction

Logistic regression, support vector machines, decision trees, random forests, gradient-boosting algorithms like XGBoost and CatBoost, and artificial neural networks are some of the supervised-learning techniques commonly used in maternal and fetal health [17]. AI is found to be widely applicable in pregnancy evaluations, preterm birth, gestational diabetes mellitus, preeclampsia, fetal growth disorders, and adverse perinatal outcomes in reviews [18–19].

Obstetric data is ideal for modeling with nonlinear and ensemble models, as it is difficult to find linear relationships among the demographic, biochemical, temporal, and imaging variables. Gradient boosting works best when the data is structured clinical data, while recurrent neural networks work well to model longitudinal EHR or biomarker trajectories [17]. Predictive analytics can be applied to maternal health, with one prospective model using 92% accuracy and an AUC-ROC of 0.94 for the prediction of multiple obstetric risks [20]. General reviews in health care are also encouraging the use of ML in clinical prediction and pathology detection and highlight the need for validation and transparency [21–22].

2.7 AI for ectopic pregnancy and CSP risk prediction

Pregnancy of unknown location is an important precursor state, as a percentage of these pregnancies are diagnosed by eventual discovery of an ectopic pregnancy. There are significant differences between the reported ectopic-pregnancy rates in PUL cases and in the general reproductive population [23]. Traditional M4 and M6 models are based on serial progesterone and β-hCG levels and will require further evaluation on multiple days in high-risk patients, potentially delaying diagnosis [24].

The team used a personalized ML model trained from its data set of 1,896 patients with PUL that tested logistic regression, XGBoost, random forest, support vector machine, and CatBoost. CatBoost's performance, based on data from its first visit, was an AUROC of 0.930 and AUPRC of 0.685, with 76.2% sensitivity and 96.6% specificity. Vaginal bleeding, progesterone, adnexal mass, gravidity, β-hCG, previous CD, previous pelvic surgery, and abdominal tenderness were important predictors. The strongest contributors were identified by SHAP analysis and were implemented as a web-based triage tool under the name of the model. The strongest contributors were identified by SHAP analysis and were implemented as a web-based triage tool, called the model.

A CSP-specific prognosis classification system was developed by combining ML with a linear score to provide a balance between prediction performance and

clinical interpretation. The morphometric parameters that were found as important predictors were the distance between the gestational sac and the uterine cavity lining, implantation-plane thickness, RMT, and gestational-sac diameter at the scar niche [25]. These objective measurements may help to guide individual treatment plans better than general visual categories.

In another study, XGBoost was applied to predict the tenderness of the uterine scar at the time of surgery in 353 women who were having repeat CD. The model achieved 86.4% accuracy, a macro-averaged F1-score of 0.83, and class-specific AUCs of 0.93, 0.87, and 0.91 [26]. SHAP showed that CD history, an inter-delivery interval less than 24 months, emergency delivery, high BMI, and placenta previa were the important predictors. The endpoint was not the development of CSP, but the study shows the feasibility of providing explainable prediction of risk of scarring in routine obstetric care.

2.8 Deep learning in obstetric imaging

Convolutional neural networks and transformer-based architectures can automate segmentation, classification, detection, and quality assessment in obstetric ultrasound [27]. Applications include first-trimester scanning, fetal biometry, echocardiography, neurosonography, placental assessment, and prediction of adverse pregnancy outcomes [10, 27]. A scoping review identified extensive research activity and reported high performance for selected fetal imaging and cardiotocography tasks, although performance varied by dataset and clinical target [27].

Multimodal architectures are particularly relevant to CSP because diagnosis depends on ultrasound morphology, hormonal biomarkers, clinical history, and temporal change. Proposed ectopic-pregnancy CDSS designs combine CNN or vision-transformer image encoders with recurrent networks for serial laboratory measurements and structured clinical features [7]. In CSP, automated measurement of RMT, gestational-sac position, implantation depth, and vascularity could reduce inter-observer variation and standardize reporting.

2.9 Scar integrity, rupture risk, and sequential prediction

RMT is one of the most clinically important surrogate measures of scar integrity. Very thin first-trimester myometrium is associated with a higher risk of PAS and complex management [2]. In a prospective study of 308 nonpregnant women with a previous low-transverse CD, the ratio of niche depth to RMT was associated with subsequent uterine dehiscence; a decision-tree threshold of 0.785 differentiated dehiscence from non-dehiscence with 71% sensitivity and 94% specificity [28].

Clinical and ultrasound variables have also been used with logistic regression, decision trees, and random forests to estimate rupture risk in scarred uteri [29]. Bayesian networks integrating sequential β-hCG and ultrasound findings achieved an AUC of 0.88 for predicting PUL outcomes in prospective validation [33]. These studies support dynamic prediction systems that update risk as new information becomes available.

2.10 Multimodal integration and explainable AI

Heterogeneous data is required to perform a proper assessment of CSP; it includes the obstetric history, symptoms, biomarkers, ultrasound or MRI and

serial measurements. Multimodal models combine these data using modality-specific encoders, early, intermediate, or late fusion. Late fusion is clinically desirable, as it can maintain the function if one modality is impaired [7].

In high-stakes obstetric care, explainability is a must. While SHAP measures the effect of structured variables on a particular prediction, Gradient-weighted Class Activation Mapping (Grad-CAM) can demonstrate which parts of an image affected a CNN-based decision [7, 24]. The integration of EHR may be able to automatically pull up prior cesarean births, inter-delivery times, placenta previa, and prior complications, minimizing manual data entry and enhancing the completeness of data [14, 26].

2.11 Clinical translation challenges

Most of the obstetric AI models have been trained in retrospective single-center data sets and not externally validated in geographically, ethnically, and clinically diverse data sets [31]. It is not a very common phenomenon, creating large, well-annotated datasets is challenging. Additional differences in imaging protocols, EHR standards, and clinical pathways limit generalizability.

When risk labels are poorly communicated, algorithmic bias can result in systematically inferior predictions for under-represented groups and amplify anxiety, or additional surveillance, or health inequalities [32]. Subgroup performance analysis, calibration, monitoring for fairness, communication to patients, cybersecurity, regulatory monitoring, and prospective clinical-impact studies are necessary for responsible implementation [15, 33].

3 RESEARCH METHODOLOGY

3.1 Review design

A structured narrative review design was adopted in this study. The evidence base comprised 32 of the sources included in the manuscript, which included material relating to the epidemiology and management of CSPs, obstetric imaging, the prediction of ectopic pregnancy, the assessment of uterine scars, the use of AI in CDSS, explainable AI, and clinical implementation. A narrative design was chosen due to the cited studies not being suitable for statistical meta-analysis, as they involved different populations, endpoints, data modalities, algorithms, and outcome measures.

3.2 Evidence organization and eligibility

If they directly contributed to at least one of four areas: (1) clinical risk, diagnosis, prognosis, or management of ectopic pregnancy; (2) AI/ML prediction relevant to the ectopic pregnancy, scar integrity, or obstetric complication; (3) ultrasound, MRI, multimodal learning, explainability, or CDSS architecture; or (4) external validation, fairness, regulation, or real-world implementation, sources were retained. Clinical context and/or translation issues were used only as filled in by editorial or general sources. The findings were themed and compared with the pre-defined research objectives.

3.3 Measurement of the research objectives

Due to the nature of this paper as a literature review, the objectives were assessed using evidence-extraction indicators instead of the new patient recruitment or model training. The measurement framework is listed in Table 1.

Table 1. RO and measurement indicators

Objective	Assessment Domain	Measurement Indicators
RO1	Clinical and diagnostic evidence	Incidence and presentation; TVUS/MRI criteria; RMT and scar morphology; sensitivity and specificity of diagnostic scores.
RO2	Predictive-model performance	AUROC, AUPRC, accuracy, sensitivity, specificity, F1-score, validation design, and important predictors.
RO3	CDSS and explainability	Data modalities; fusion approach; SHAP/Grad-CAM; EHR integration; usability; missing-data handling; and workflow support.
RO4	Clinical translation	External validation; dataset diversity; calibration; fairness; regulation; prospective impact; and implementation readiness.

3.4 Data extraction and synthesis

From each study, the review identified the clinical target, study population or setting (if reported), input variables, algorithm or approach to decision support, reported method for validation, measures of predicted performance, method of explainability, and evidence for implementation. Key quantitative metrics included were sensitivity, specificity, accuracy, AUROC, AUPRC, and F1 score. The qualitative indicators were multimodal data, integration of the EHR system, external validation, fairness, ease of use for clinicians, regulatory considerations, and prospective impact evaluation.

The synthesis was descriptive, not pooled. The reported metrics were only used as indicators of model potential due to the various clinical endpoints, class distributions, sample sizes, and validation approaches across the different studies. Results are then focused on performance and evidence quality.

4 RESULTS

4.1 RO1: Clinical and diagnostic determinants of CSP risk

Consistent findings across these groups of authors were that previous CD, scar morphology, location of the gestational sac, RMT, scar depth, peritrophoblantic vascularity, vaginal bleeding, β-hCG, fetal cardiac activity, gestational age, and associated placental abnormalities were important in making the diagnosis or predicting prognosis [2, 8, 11, 25, 33]. TVUS is the main diagnostic tool used, with MRI being most useful in cases where the anatomy and/or invasion cannot be adequately assessed by TVUS [9–10]. Objective morphometric variables are particularly well suited for AI, as they can be measured continuously but need not be assigned to the general category of visual variables.

4.2 RO2: Predictive performance of AI and ML models

The strongest directly relevant ML evidence came from ectopic-pregnancy and scar-related prediction studies. The CatBoost PUL model reported an AUROC of 0.930, an AUPRC of 0.685, 76.2% sensitivity, and 96.6% specificity [24]. The XGBoost scar-tenderness model reported 86.4% accuracy, a macro-averaged F1-score of 0.83, and class-specific AUCs between 0.87 and 0.93 [26]. A Bayesian network for PUL outcome prediction achieved an AUC of 0.88 in prospective validation [30]. A clinical ultrasound CSP score reported 95.6% sensitivity and 91.7% specificity [11]. These results show useful discrimination, but they do not establish a single best model because the endpoints and cohorts differed.

Tree-based ensembles were particularly effective for structured clinical data, whereas neural and transformer-based approaches were more appropriate for imaging or longitudinal data [27]. The findings support a hybrid strategy in which structured clinical variables, serial biomarkers, and image-derived morphometric features are processed by specialized models and combined into a final risk estimate.

4.3 RO3: Multimodal, explainable, and workflow-integrated CDSS

The reviewed literature supports a multimodal CSP-CDSS architecture containing four components: an imaging module for ultrasound or MRI; a temporal module for serial β-hCG or other biomarkers; a structured-data module for symptoms and obstetric history; and a fusion layer that generates calibrated risk categories and management-oriented alerts [3]. Explainability can be provided through SHAP for tabular variables and Grad-CAM or related saliency methods for imaging [4, 24].

Clinical workflow evidence remains limited but encouraging. ISAS improved pregnancy-location and ectopic-pregnancy diagnosis among non-expert trainees [16], and the PUL model was implemented as a web-based triage platform [24]. EHR integration can reduce manual data entry and enable longitudinal updating, although interoperability and data quality are unresolved [14].

4.4 RO4: Validation and implementation readiness

The major drawbacks were single-center retroactive design, small study size, lack of uniformity in endpoints, limited calibration details, poor external validation, and poor prospective impact assessment [15, 31, 32]. The issue of fairness and the performance of subgroups was also rarely reported when there were clinical and ethical implications for incorrect high-risk pregnancy labelling [32]. Overall, this evidence suggests that there is good evidence for technical promise but insufficient evidence for autonomous routine use.

5 DISCUSSION

5.1 Interpretation of the main findings

According to the review, AI can supplement the information that clinicians already use but may be analyzed separately to improve CSP risk stratification. Ultrasound

morphology refers to the anatomy of the implantation site and scar, biochemical markers are represented by β-hCG and progesterone, symptoms and obstetric history give background information on the risk, and longitudinal measurements show the development of the disease. AI can be most useful when it combines all this data, measures uncertainty, and offers clear decision-making support—not in place of the clinical decision-making.

While the AUROC results of selected studies are favorable, it is insufficient to be reported by the performance metrics. A model may be well discriminating but poor at calibration, unclean, and/or unreliable in a new population. Future studies should therefore include calibration plots or scores, decision-curve analysis, confidence intervals, how the data were handled in case of missing, class imbalance, and subgroup performance, as well as AUROC.

5.2 Clinical implications

A clinically helpful CSP-CDSS should assist in making several decisions: 1) the need for urgent specialist consultation; 2) if the pregnancy is likely to be deeply implanted or associated with PAS; 3) if they consider it appropriate to arrange for fertility-preserving treatment; and 4) if surgery, blood products, interventional radiology, or multidisciplinary care is warranted. The system should display the forecasted risk, the factors contributing to that risk, evidence via images, evidence about data quality, and a clear message that the output does not replace a clinical assessment.

There is a need for a standardized way to acquire the ultrasound data for reliable automatic analysis. Reproducible measurements like (RMT), (gestational-sac distance from uterine cavity), (implantation-plane thickness), (niche depth), (sac diameter), and vascular indices should be emphasized in the development of the model [8, 25, 28]. These measurements can also help to standardize measurements across institutions and serve as a set of longitudinal markers for dynamic risk updating.

5.3 Limitations of the current evidence and this review

Evidence is varied, ranging from studies specifically on CSP to ectopic-pregnancy models, scar-integrity studies, obstetric imaging studies, and general pregnancy CDSS reviews. Several of them therefore have to be transferred by clinical analogy to CSP populations. The review also does not contain a registered protocol, a PRISMA flow diagram, or a formal risk-of-bias scoring or meta-analysis. The performance measures reported must therefore be viewed as evidence of performance rather than as aggregated measures.

5.4 Future research priorities

Future studies should establish multicenter CSP registries with standardized ultrasound protocols, common definitions, treatment labels, and clinically meaningful outcomes. External validation should include different equipment vendors, sonographer experience levels, ethnic groups, healthcare systems, and resource settings. Federated learning may facilitate multicenter development without centralizing sensitive data, while transfer learning may reduce the number of CSP-specific images required for model training.

Prospective studies should compare AI-assisted care with standard care using outcomes such as diagnostic delay, severe hemorrhage, unplanned hysterectomy, fertility preservation, referral time, clinician workload, patient understanding, and cost-effectiveness. Continuous monitoring for dataset drift, calibration failure, unfair subgroup performance, and inappropriate automation is also required after deployment.

6 CONCLUSION

AI-based risk stratification has the potential to make the assessment of uterine scar pregnancy more objective, reproducible, personalized, and clinically actionable. The most informative inputs are likely to include standardized ultrasound morphology, RMT and other scar measurements, serial hormonal biomarkers, symptoms, and previous obstetric history. Tree-based ML models perform well with structured clinical data, while deep learning can support automated imaging analysis and multimodal fusion.

Eligibility criteria for the review objectives were determined by clearly defined diagnostic, predictive, explainability, validation, and implementation criteria. While selected studies have reported high discrimination (AUROC near to or above 0.90), heterogeneous endpoints and small external validation mean that these studies cannot be directly compared and cannot be used routinely in autonomous deployment. The best near-term fit is explainable CDSS helping clinicians' triage, measure in a standard way, communicate risk, and plan with other providers.

The datasets needed for clinical translation will be multicenter, definitions will be standardized, prospective impact studies will be required, datasets will need calibration and fairness assessment, EHR interoperability will be required, regulatory compliance will be necessary, and clinical monitoring will need to be undertaken following the deployment. These protections would lead to a decrease in diagnostic delay, better treatment planning, less severe maternal morbidity in CSP, and less protection of fertility in CSP with AI-enhanced CDSS.

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