Original Paper

Multistakeholder Expectations and Implementation Concerns Regarding AI-Based Pregnancy Risk Assessment in Maternity Care: Qualitative Descriptive Study

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Abstract

Background: Pregnancy risk assessment requires not only accurate identification of risk but also communication, referral, and follow-up across different levels of care. Although AI-based tools are increasingly proposed to support this process, evidence remains limited on how women, primary health care professionals, and hospital-based maternity care providers expect AI-generated risk information to be interpreted and used in care, as well as on what conditions they consider important for its practical use.

Objective: This study aimed to explore multistakeholder expectations and anticipated implementation concerns regarding AI-based pregnancy risk assessment in maternity care, with particular attention to how AI-generated risk information could be interpreted, confirmed, and used to inform care decisions and subsequent management.

Methods: This qualitative descriptive study used semistructured interviews with 93 participants in Guizhou Province, China, including 33 (33.5%) pregnant or postpartum women, 23 (24.7%) primary health care professionals, and 37 (39.8%) hospital-based maternity care providers. Purposive sampling with maximum variation was used. Participants were recruited from 18 health care facilities, including primary health care facilities and secondary and tertiary hospitals. Interviews were conducted between August 30, 2024, and May 2026. Brief standardized conceptual material was used to support discussion of AI-based pregnancy risk assessment; it did not depict a specific product or prototype. Data were analyzed using inductive qualitative content analysis.

Results: Five descriptive themes and 16 subthemes were developed. The expected value of AI-based pregnancy risk assessment depended on whether it addressed practical gaps in pregnancy risk management, although priorities differed across stakeholder groups. Women emphasized understandable risk information and care-seeking guidance; primary health care professionals emphasized referral, feedback, and follow-up continuity; and hospital-based providers valued clinically interpretable information for assessment, management, and cross-level coordination. Participants valued early and dynamic risk recognition because pregnancy risk could emerge, worsen, or be reclassified as pregnancy progressed, making sustained visibility of risk information important. AI-generated risk information was not treated as self-evident; it needed to be interpreted and confirmed in relation to women's bodily experience, clinicians' judgment, examination results, referral rules, and higher-level confirmation. Risk recognition was considered useful when it could be translated into guidance, referral,

feedback, and follow-up. Implementation concerns centered on risk communication and anxiety management for women and on workload, usability, training, and organizational support for health care professionals.

Conclusions: Stakeholders expected AI-based pregnancy risk assessment to provide risk information that could become meaningful and actionable within existing maternity care pathways. Future AI tools in maternity care should therefore be evaluated not only for predictive accuracy but also for whether risk information can be understood, communicated, confirmed, and carried forward into follow-up and coordinated action across levels of care.

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Introduction

Timely identification of pregnancy-related risks is an important component of antenatal care [1]. AI and machine learning (ML) methods are increasingly being investigated in pregnancy care for risk prediction and clinical decision support [2,3]. Systematic reviews have identified a growing range of pregnancy-related AI and ML applications, while also highlighting limitations in user testing, external validation, and real-world implementation [2,3].

Digital approaches relevant to pregnancy and maternal risk management include web-based risk assessment and education [4], digital systems supporting pregnancy risk management [5], and ML- or AI-augmented clinical decision support systems [2,3]. Within this broader landscape, AI-based pregnancy risk assessment refers here to the use of AI methods to generate a pregnancy-related risk estimate, such as a risk probability or risk-level prompt, from pregnancy-related health information. This focus is distinct from other digital functions used to record, display, or communicate health information. Because such risk estimates would be introduced into existing maternity care processes rather than used in isolation, their prospective implementation also raises questions about how different users may engage with them in practice [6,7].

A qualitative systematic review of clinical AI implementation identified multiple stakeholder groups and a wide range of context-dependent implementation factors [6]. In maternity care, a systematic review of qualitative studies on clinical decision support tools similarly identified user- and setting-related factors relevant to their acceptability, usability, and implementation [7]. Qualitative inquiry can therefore complement technical evaluation by examining proposed technologies from the perspectives of those who may encounter them in practice [6,7].

Empirical stakeholder research on AI in obstetric and perinatal care is growing. Pregnant women's perspectives have been examined in studies of AI use in clinical care and intelligent pregnancy applications [8,9], while maternity professionals have been interviewed about hypothetical obstetric AI and an AI-driven cardiotocography decision support system [10,11]. More recent research has incorporated patients and health care professionals into the development and implementation planning of an ML algorithm for first-onset perinatal depression [12], and a 2026 qualitative study additionally included AI developers using a postpartum depression risk algorithm as a case study [13]. These studies show that patient and multistakeholder perspectives are already represented, but their questions and use cases differ: some studies address general attitudes toward AI or intelligent pregnancy applications, whereas others focus on specific use cases, such as hypothetical obstetric AI, AI-driven cardiotocography, or perinatal depression prediction [8-13]. The recent prediction-focused studies included patients and mixed professional groups, and one also included AI developers, but neither was designed to compare perspectives across primary- and hospital-level maternity care within the same care system [12,13]. This leaves limited empirical understanding of how women, primary health care professionals, and hospital-based maternity care providers, positioned across different levels of maternity care within a common risk-management framework, view the prospective use of AI-based pregnancy risk assessment [8-13].

This question is particularly relevant in China, where pregnancy risk assessment and management are embedded within a national stratified framework. National guidance specifies pregnancy risk screening and assessment, 5-color risk classification, dynamic reassessment, and tiered management according to risk level, with responsibilities distributed across different levels of maternity care [14]. The 2021-2025 Maternal and Infant Safety Action Improvement Plan further reinforced standardized pregnancy risk screening and assessment and multidisciplinary dynamic assessment and management [15]. Digital systems have also been developed to support this framework; for example, a provincial maternal and child health information system in Inner Mongolia incorporates 5-color pregnancy risk management and cross-institutional data interconnection [5]. This established framework provides the clinical and organizational context in which the prospective use of AI-based pregnancy risk assessment can be considered and understood. Examining these stakeholder perspectives together can help identify how expectations for interpreting risk and responsibilities for subsequent care connect across roles and levels of care.

This qualitative descriptive study aimed to explore the expectations and anticipated implementation concerns of multiple stakeholder groups, including pregnant and postpartum women, primary health care professionals, and hospital-based maternity care providers, regarding AI-based pregnancy risk assessment in maternity care, with particular

attention to how AI-generated risk information could be interpreted, confirmed, and used to inform care decisions and subsequent management.

Methods

Study Design and Setting

This qualitative descriptive study used semistructured interviews to explore multistakeholder expectations and implementation concerns regarding AI-based pregnancy risk assessment in maternity care. This approach was appropriate because the study aimed to provide a straightforward, relatively low-inference account that remained close to participants' own descriptions [16-18]. Inductive qualitative content analysis was selected because it was consistent with this descriptive aim and allowed related meanings to be systematically synthesized while remaining relatively close to participants' accounts [16,19]. Including 3 stakeholder groups also allowed similarities and differences across perspectives to be examined.

The study was conducted between August 30, 2024, and May 2026 in Guizhou Province, southwest China. Guizhou has a substantial rural population and an extensive primary health care network, with maternity care delivered across primary, secondary, and tertiary levels amid continuing regional and urban-rural differences in health care resource distribution [20,21]. This provided a relevant setting for examining how pregnancy risk information may be interpreted and acted on across different levels and contexts of care. Participants were recruited across 18 health care facilities in urban and rural settings. Facilities were identified to support variation in level of care and service context, while practical access and feasibility also influenced which settings could be included. Access arrangements varied across settings and included existing contacts of the research team, professional contacts, and direct approaches. Where applicable, an official letter of introduction from the researchers' institution was provided, and locally required administrative procedures were followed before facility-based recruitment.

Of the 102 eligible individuals approached, 4 declined to participate. Of the remaining 98 individuals who initially agreed to participate, 5 (5.1%) were not included in the final analysis. One (1.0%) pregnant woman left before the interview began because of an unexpected commitment. Four interviews, involving 1 tertiary hospital nurse, 1 midwife, 1 county-level obstetric doctor, and 1 pregnant woman, were interrupted or ended prematurely because of urgent duties, time pressure, or other immediate commitments. As these interviews did not cover the key sections of the interview guide or provide sufficient data relevant to the study aim, and follow-up interviews could not be arranged, the final analytic dataset comprised 93 participant cases. These cases were based on 93 completed initial interviews, and 7 participants also contributed a brief follow-up interview.

Participants and Sampling

Participants comprised pregnant or postpartum women, primary health care professionals involved in maternal health services, and hospital-based maternity care providers, including obstetricians, midwives, obstetric nurses, and outpatient maternity nurses. Purposive sampling with maximum variation was used. Depending on the setting, potentially eligible participants were identified with assistance from local health care staff, through participant referrals or professional contacts, or by direct approach. A member of the research team then confirmed eligibility, explained the study, and obtained informed consent. Among pregnant and postpartum women, maximum variation was sought in pregnancy/postpartum stage, age, parity, pregnancy risk level, major pregnancy complications, and singleton/multiple pregnancy. Among health care professionals, maximum variation was sought in professional role, facility level, age, gender, and years of professional experience.

Sample adequacy was considered with reference to the concept of information power [22]. Given the broad multistakeholder aim and the need to capture variation within and across stakeholder groups, a relatively varied sample was sought. Recruitment and analysis proceeded iteratively.

Recruitment occurred in 3 phases. The main recruitment phase took place from August 30, 2024, to January 2025. Ongoing analysis indicated that accounts from women with moderate or high pregnancy risk were relatively underrepresented in the earlier interviews; 8 additional women with moderate or high pregnancy risk were therefore purposively recruited in July 2025. During later analysis, village-level accounts remained relatively limited, and early interviews suggested overlap in the day-to-day work described by staff with different formal roles. Three additional village doctors, each from a different village clinic, were therefore purposively recruited in May 2026 to increase variation and depth in village-level accounts.

Eligibility Criteria

For health care professionals, inclusion criteria were (1) current employment in a maternal health care–related role; (2) direct involvement in maternal health management or service delivery for at least 6 months; and (3) willingness to participate in an interview and provide informed consent. For women participants, inclusion criteria were (1) receiving maternity care during pregnancy, childbirth, or within 42 days postpartum; (2) ability to participate in an interview in Mandarin Chinese or a local Chinese dialect; and (3) willingness to participate and provide informed consent. Exclusion criteria for all participants included inability to complete the interview because of urgent circumstances, declining participation, or withdrawal of consent at any stage. Participant characteristics are summarized in Table 1.

Table 1. Participant characteristics by stakeholder group.

Characteristic	Pregnant or postpartum women (n=33)	Primary health care professionals[a] (n=23)	Hospital-based maternity care providers (n=37)
Age (years), mean (SD)	30.4 (4.5)	36.4 (8.7)	36.6 (7.7)
Gender, n (%)			
Female	33 (100)	19 (82.6)	34 (91.9)
Male	0 (0)	4 (17.4)	3 (8.1)
Education level, n (%)			
Technical secondary school or below	9 (27.3)	4 (17.4)	0 (0)
Junior college/bachelor's degree	22 (66.7)	19 (82.6)	31 (83.8)
Master's degree or above	2 (6.1)	0 (0)	6 (16.2)
Marital status, n (%)			
Married	33 (100)	20 (87.0)	30 (81.1)
Unmarried/divorced/widowed	0 (0)	3 (13.0)	7 (18.9)
Pregnancy status, n (%)			
Pregnant	18 (54.5)	—[c]	—
Postpartum	15 (45.5)	—	—
Highest recorded or reported pregnancy risk level before interview[b], n (%)			
Green	10 (30.3)	—	—
Yellow	10 (30.3)	—	—
Orange	9 (27.3)	—	—
Red	4 (12.1)	—	—
Purple[d]	2 (6.1)	—	—
Professional role, n (%)			
Village doctor	—	4 (17.4)	—
Village nurse	—	2 (8.7)	—
Township/community doctor	—	9 (39.1)	—
Township/community nurse or midwife	—	8 (34.8)	—
Hospital obstetrician	—	—	17 (45.9)
Hospital nurse or midwife	—	—	20 (54.1)
Years of professional experience, median (IQR; range)	—	6 (4-13; 1-33)	11 (4-16; 1-33)

[a]Primary health care facilities included village clinics, township health centers, and community health service centers.
[b]For women, green, yellow, orange, and red refer to the highest recorded or reported pregnancy risk level before interview and do not represent a fixed risk status throughout pregnancy.
[c]Not applicable.
[d]Purple denotes infectious disease–related risk and could coexist with another color-coded risk level; therefore, percentages for pregnancy risk level may exceed 100%.

Data Collection

Data were collected through semistructured individual interviews, each conducted by 1 of 5 trained members of the research team with backgrounds in nursing, maternal health, or qualitative research. All 5 interviewers contributed to the main recruitment phase. Three (60%) of the 5 interviewers participated in the 2 later recruitment phases, with most interviews in these phases conducted by Z Luo. All interviewers had prior training in qualitative research and received additional study-specific training on the interview guide, interviewing techniques, and the use of prompts and probes. No formal researcher–participant relationship was established before the interviews. Interviews were conducted mainly face-to-face in private rooms at participating facilities. Two initial interviews were conducted online when distance or scheduling made in-person interviews impractical, and 7 (7.5%) participants completed brief follow-up interviews to clarify or deepen issues raised in the initial interviews. Six follow-up interviews were conducted via telephone in September 2024, and 1 with a village doctor was conducted face-to-face in 2026. Follow-up interviews were conducted by the same interviewer as the initial interview and addressed participant-specific points about roles, referral and confirmation, or information transfer. Total interview time per participant, including follow-up interviews where applicable, ranged from 25 to 117 minutes, reflecting differences in participants' roles and available time.

The interview guide was developed through literature review and discussion within the research team. The literature and policy documents reviewed during guide development

included work on pregnancy risk assessment and management in China [14,15], digital monitoring and continuity of care in high-risk pregnancy [23], digital implementation and workflow in antenatal care [24], AI-supported clinical decision-making in pregnancy care [2,11], clinician trust in predictive clinical decision support [11,25], and women's needs for pregnancy risk information, communication, and follow-up [23,26]. The guide was discussed and refined within the research team and pilot-tested with a small number of participants from the target groups. Six pilot interviews were conducted across the 3 stakeholder groups and retained in the final analysis because no substantive changes were made to the interview topics. The final interview guide is provided in Multimedia Appendix 1. The guide was used flexibly, with question wording, sequence, and depth adapted to participants' responses. Topics combined in a prompt could be explored separately, and probes sought clarification, concrete examples, and further details about decisions and care processes.

Interviews followed a staged semistructured guide. Participants first described their experiences of pregnancy risk assessment and maternity care, including risk identification, care-seeking or service provision, follow-up, referral, feedback, and the use of existing pregnancy-related digital tools or clinical support resources. This discussion took place before the AI-related stimulus material was introduced. For the subsequent discussion, participants were shown the same brief standardized stimulus material introducing the concept of AI-based pregnancy risk assessment. The participant-facing material comprised a brief interview overview and illustrative descriptions of possible functions, including maternal health records, AI-based risk estimation, visual and textual risk reports, and health education or general care information. The original Chinese material and an English translation are provided in Multimedia Appendix 2.

AI-based risk estimation was described as using available pregnancy-related information to generate a risk probability or risk-level prompt. The material served as a discussion stimulus; it did not depict a specific product or prototype, nor did it represent an operational or validated system or a clinical recommendation. It did not include screenshots of an operational AI system, AI model diagrams, specific example risk scores, color-coded AI outputs, clinical scenarios, or model performance information. In line with the use of vignettes or stimulus materials in qualitative research, this approach was used to support discussion among participants with varying levels of prior familiarity with AI tools [27]. The standardized material was available in both printed and electronic formats. Participants were then asked to discuss the tool's potential value, concerns, feasibility, and conditions for use. Interviews were conducted in Standard Mandarin Chinese or local Chinese dialects spoken in Guizhou. Audio recordings were transcribed verbatim in Chinese, preserving participants' colloquial expressions and dialect usage. Transcripts were checked against the audio recordings for accuracy and deidentified before analysis. Where a dialect term had no standard written Chinese form, pinyin with a brief explanatory note was used.

Data Analysis

Data were analyzed using inductive qualitative content analysis [28]. Data collection and preliminary analysis proceeded concurrently and iteratively. As data collection progressed, transcripts were reviewed and preliminarily coded, and ongoing analysis informed subsequent data collection and recruitment.

All coding and qualitative analysis were conducted using the original Chinese transcripts. Transcripts were read repeatedly to gain an overall understanding of the data. Meaning units relevant to the study aim were identified and condensed while preserving their core meaning, and initial codes were assigned [29]. Codes were compared within and across transcripts. Related codes were grouped into subthemes, which were further developed into broader descriptive themes [19,29]. The resulting descriptive themes synthesized recurrent patterns across participants' accounts while remaining relatively close to the data and involving less interpretation than more interpretive themes of meaning [19,30]. As additional transcripts were analyzed, codes, subthemes, and descriptive themes remained open to revision. The developing analytic structure was repeatedly checked against the original transcripts and refined through analytic discussions. MAXQDA (VERBI GmbH) was used to organize and manage the data.

Z Luo led the coding and analysis of the full dataset. Four other team members contributed to the coding of selected transcripts and to discussions of coding and interpretation. Coding decisions and developing interpretations were discussed within the research team and further reviewed with Z Li. Illustrative examples of the analytic progression from meaning units to condensed meanings, codes, subthemes, and descriptive themes are provided in Multimedia Appendix 3. Analysis considered patterns within each stakeholder group as well as similarities and differences across the 3 stakeholder groups in developing the overall findings.

Quotations selected for publication were translated into English by Z Luo during manuscript preparation. Culturally or institutionally specific terms were translated according to their meaning in the Chinese maternity care context, with brief explanatory wording used where a direct English equivalent was not appropriate. AI-assisted language editing was limited to refining the English wording. Another author checked the final English quotations against the corresponding Chinese excerpts for consistency of meaning.

Researcher Reflexivity

The research team comprised members with backgrounds in nursing, maternal health, and qualitative research, which shaped both data collection and interpretation. Z Luo, the primary analyst, was a female doctoral candidate with prior experience in qualitative research and personal experience of pregnancy and maternity care. This background supported sensitivity to issues of maternal care, risk communication, and provider decision-making but also required ongoing reflexive attention to avoid imposing prior assumptions on participants' accounts. Two team members with clinical backgrounds

brought service delivery and risk management perspectives to the analysis; these perspectives were made explicit and critically examined during team discussions. Z Li, a professor of nursing and experienced qualitative researcher, provided methodological oversight and challenged clinically dominant or overly instrumental interpretations where necessary. Other team members contributed relatively less clinically embedded perspectives that helped question taken-for-granted assumptions during analysis.

To address the potential influence of researcher positionality, reflexive notes were maintained throughout data collection and analysis, documenting prior assumptions, immediate impressions, emotional responses, and evolving interpretations. These reflections were discussed in regular analytic meetings to enhance transparency and keep interpretations grounded in participants' accounts.

Trustworthiness

Trustworthiness was addressed in relation to credibility, dependability, confirmability, and transferability. Credibility was addressed through the analytic procedures described in the Data Analysis section; illustrative quotations are presented in the Results to show how the findings are grounded in participants' accounts. Dependability and confirmability were supported by retaining coding records and notes from analytic discussions to document key analytic decisions. Transferability was supported by purposive maximum-variation sampling within stakeholder groups and detailed descriptions of the study setting, participant characteristics, and sampling process.

Ethical Considerations

Ethical approval was obtained from the Ethics Committee of Guizhou Medical University (approval 2024-219) on August 26, 2024. Recruitment and data collection, including the later phases through May 2026, were conducted under this approved protocol. All participants provided informed consent before participation. They were informed of the study purpose, procedures, the voluntary nature of participation, and their right to withdraw at any time without penalty. Confidentiality was protected through the use of participant codes and the removal of identifying information from transcripts. All study materials were stored in password-protected files accessible only to the research team. Pregnant women were specifically assured that participation or nonparticipation would not affect their clinical care.

Results

Overview

A total of 93 participants were interviewed, including 33 (35.5%) women, 23 (24.7%) primary health care professionals, and 37 (39.8%) hospital-based maternity care providers. Participant characteristics are presented in Table 1. Five descriptive themes and 16 subthemes were developed (Textbox 1). Figure 1 illustrates how participants expected AI-generated pregnancy risk information to move from prediction toward action through 5 interrelated themes.

The figure summarizes the relationships among the 5 themes. Participants expected AI-generated pregnancy risk information to become useful when it addressed practical gaps, supported early and dynamic recognition, remained visible over time, could be interpreted and confirmed by relevant actors, and could be translated into action through guidance, referral, feedback, follow-up, coordination, and reminders. Emotional burden, workload, usability, training, role clarity, and workflow support shaped whether this movement from prediction to action would be feasible.

Textbox 1. Summary of themes and subthemes.

Theme 1: Expected to address practical gaps in pregnancy risk management
- Primary health care professionals expected AI-based pregnancy risk assessment results to fit within existing screening, referral, confirmation, and feedback pathways
- Hospital-based maternity care providers valued integrated pregnancy information and updated risk assessment for clinical management
- Pregnant women expected understandable risk information and accessible support for care-seeking decisions

Theme 2: The value of dynamic risk recognition and sustained visibility
- Early risk recognition and timely response
- Pregnancy risk as dynamic and continuously evolving
- Continuous visibility of changing risk across ongoing care

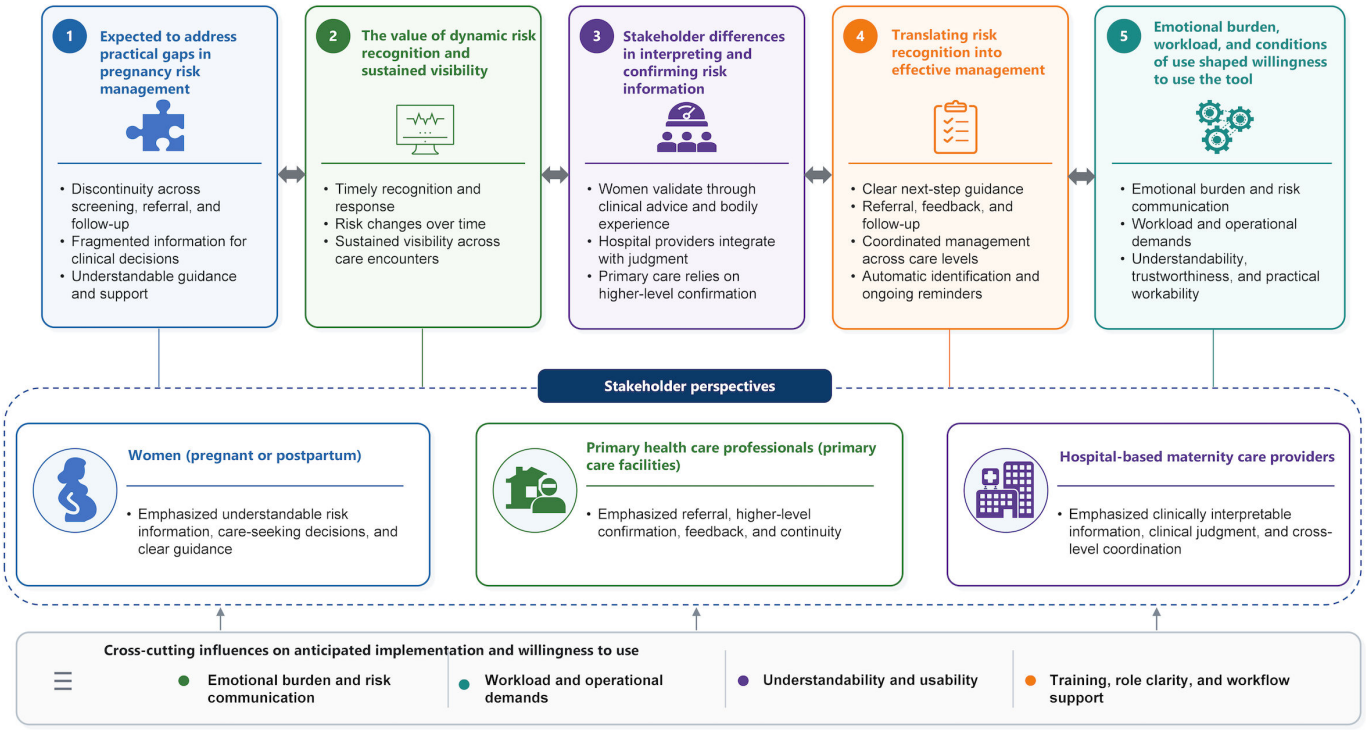
Theme 3: Stakeholder differences in interpreting and confirming risk information
- Women's validation of AI-generated risk information through clinical advice and bodily experience
- Clinical judgment remained central in the use of AI-generated risk information in hospital care
- Reliance on higher-level confirmation in interpreting and acting on risk in primary care

Theme 4: Translating risk recognition into effective management
- From risk assessment to clear next-step guidance
- Risk recognition carried forward through referral, feedback, and follow-up
- Cross-level information transfer and coordinated decision-making
- Automatic identification and reminders to support everyday risk management

Theme 5: Emotional burden, workload, and conditions of use shaped willingness to use the tool

- Risk prompts as both support for timely action and a source of anxiety
- Balancing anticipated workload reduction against additional operational demands
- Making AI-based assessment understandable, trustworthy, and workable in practice

Figure 1. From risk recognition to action: stakeholder expectations and implementation influences for AI-based pregnancy risk assessment. Arrows between themes indicate analytic relationships rather than a fixed sequence. The bottom row elaborates the cross-cutting influences captured in theme 5.



Theme 1: Expected to Address Practical Gaps in Pregnancy Risk Management

Overview

Participants' expectations for AI-based pregnancy risk assessment were closely tied to difficulties in existing pregnancy risk management. Their accounts included both risk assessment itself and the supporting functions needed for risk information to be used in care. Primary health care professionals emphasized links between initial screening, referral, higher-level confirmation, feedback, and continued follow-up. Hospital-based maternity care providers wanted pregnancy records and examination results to be easier to review together, with risk assessment updated as new information became available and used to support clinical management. Participants' descriptions of existing risk classifications also illustrated the management context into which AI-generated risk information would need to be integrated. Pregnant women wanted risk information that helped them understand their situation and easier access to professional advice when needed.

Primary Health Care Professionals Expected AI-Based Pregnancy Risk Assessment Results to Fit Within Existing Screening, Referral, Confirmation, and Feedback Pathways

For primary health care professionals, the anticipated use of AI-based pregnancy risk assessment was considered in relation to existing pathways of risk management. Primary-level facilities were involved in registration and initial screening, while confirmation and risk grading often relied on higher-level hospitals. Participants' accounts therefore highlighted that AI-based pregnancy risk assessment results would need to be incorporated into referral, higher-level confirmation, feedback, and subsequent follow-up rather than used independently of these existing processes.

A primary care doctor described this pathway as a sequence of referral, confirmation, return of results, and continued management:

> *We usually refer the woman to the higher-level facility. After they've looked at her and confirmed it, they send the result back down to us, and then we continue the follow-up management... We update the risk level, and only women at the green level are suitable for care here.*
> *[D14, physician, central township health center]*

Hospital-Based Maternity Care Providers Valued Integrated Pregnancy Information and Updated Risk Assessment for Clinical Management

When considering how the proposed AI-based pregnancy risk assessment might be used in clinical work, hospital-based maternity care providers wanted pregnancy-related information to be brought together in a form that was easier to review. They described the importance of viewing previous antenatal records and examination results together and expected risk assessment to be updated as new information became available. They also linked different risk classifications to differences in examination, monitoring, and clinical management.

A tertiary hospital doctor linked risk classification directly to clinical management, rather than treating it as a label in itself:

> *Different comorbidities and different colors mean different principles for how we manage the patient. For example, when a red high-risk patient comes in, the examinations, nursing care, and monitoring we provide are all handled differently.*
> *[D6, obstetric doctor, tertiary hospital]*

Another doctor described a system in which new examination results could lead to reassessment and alert clinicians when the risk level changed:

> *All the examination results would be shown in the software system, and the system would automatically assess which five-color risk category the woman belongs to... If something is wrong with the result, the system would automatically reassess it, see whether the risk level has changed, and if it has changed, it could remind us doctors.*
> *[D13, doctor, tertiary hospital]*

Nurses and midwives similarly valued having longitudinal pregnancy-related information available in a form that was easier to review. One nurse-midwife described being able to review changes in clinical indicators without examining each report separately:

> *I think it would be very meaningful. At least, if this form were filled in regularly, we could see how the woman's condition changed over time. As soon as I opened it, I could see how her coagulation had changed, how her liver function had changed, and whether her urine protein had increased. I could see all of that... We wouldn't have to go through the reports one by one.*
> *[B11, nurse/midwife]*

Pregnant Women Expected Understandable Risk Information and Accessible Support for Care-Seeking Decisions

Pregnant women spoke about the tool in more immediate and practical terms, focusing on whether it could help them understand their situation and obtain further guidance when needed.

For some women, the usefulness of the tool lay in making risk information easier to understand. One woman explained that if the tool could complete the assessment and show the result, "then you'd have some sense of what's going on" (P13, pregnant woman, 39 weeks). Women also described consultation with health care professionals as a way of obtaining further guidance after receiving a result. When in-person care was inconvenient, 1 pregnant woman felt that online expert consultation through the platform would be useful because "it would also save you time, which would be really good" (P11, pregnant woman, 38 weeks). Another woman described how online consultation based on test results could reduce the time spent on registration and travel:

> *Actually, even getting an appointment now wastes a lot of time. If I could consult online instead of coming here in person, I'd be really happy. Once my report comes out, I could consult the relevant doctor based on the test results... Even if it were paid, I'd still be willing.*
> *[P19, pregnant woman, 36 weeks]*

Theme 2: The Value of Dynamic Risk Recognition and Sustained Visibility

Pregnancy risk was described as something that could appear, worsen, or be reclassified as pregnancy progressed. In discussing AI-based pregnancy risk assessment, participants drew on experiences of changing risk in existing care and emphasized timely recognition, reassessment as new information emerged, and continued visibility of risk information.

Early Risk Recognition and Timely Response

The value of early recognition was most clearly expressed in situations where delay could affect what happened next. For hospital staff, this meant identifying critical illness or risk progression before the woman's condition worsened. A tertiary hospital nurse summarized this as "In the hospital, its value is that it helps us find her critical condition in time" (N1, nurse, tertiary hospital), while others linked early recognition to prevention and intervention.

Pregnant women described timeliness less as a clinical classification issue and more as a question of what to do when something felt wrong. One pregnant woman said that a medium- or high-risk result could prompt women to seek care promptly rather than wait:

> *If the assessment indicates medium or high risk, then please go to the hospital quickly. Don't just tough it out by yourself, because many people think, "It's nothing, I*

can bear it..." Some people may think it will be better tomorrow, but then they may miss the moment when the baby is asking for help.
[P7, pregnant woman, 39 weeks]

Another woman similarly connected timely alerts with early intervention:

If it could assess whether there is a problem and give timely reminders—and if there is a problem, allow early intervention and prevention—that would be quite good.
[P21, pregnant woman, 14 weeks]

Pregnancy Risk as Dynamic and Continuously Evolving

Participants' accounts also pointed to the need for risk assessment to respond to changes as they emerged, including new symptoms, test results, and obstetric events. A tertiary hospital nurse described this through the movement between color-coded risk levels:

It's a dynamic observation and assessment of pregnant women... for example, if she is currently at yellow risk and it isn't picked up in time, could she progress to red risk?
[N2, nurse, tertiary hospital]

Doctors gave similar examples from clinical practice. One described a woman who initially appeared to be low risk but was later reclassified after laboratory results showed hypothyroidism requiring medication:

At first this patient looked fine, but later her blood tests showed hypothyroidism, and it had reached the point where medication was needed. Then green would become orange.
[D2, obstetric doctor, tertiary hospital]

Another doctor described rapid change as a feature of obstetric care itself:

The biggest challenge in obstetrics is that things can change in an instant. It's not something you can simply predict step by step. A woman may look fine now, but once labor starts, a new problem may suddenly come up.
[D5, obstetric doctor, tertiary hospital]

Continuous Visibility of Changing Risk Across Ongoing Care

For participants, risk changes also needed to remain visible after they had been identified. In ward care, visualization was valued because it made the risk status immediately recognizable to both staff and women:

Visualizing pregnancy risk status is really good, because it is simple and clear. The patient can see it, and the nurse can see it too, so we know this is a critically ill patient and a high-risk situation.
[N3, nurse, tertiary hospital]

Visibility also mattered when earlier risk information still had implications for later care. A nurse described how seeing the risk trajectory from the beginning could help staff anticipate possible deterioration:

If the pregnancy risk tool is used from the beginning, and after filling it in you can see that she is high-risk later on, then you can already be mentally prepared that her condition may change.
[N4, nurse, tertiary hospital]

When asked whether previously recorded high-risk information should still be visible even if the woman was currently categorized as low risk, she answered: "Yes, we would still pay more attention" (N4, nurse, tertiary hospital).

Another nurse/midwife described how a dynamic display could help ward nurses become aware of high-risk situations earlier:

If it's used on the ward, and a high-risk situation could show up as things change, the nurse on duty could know about it earlier. If the doctors update the patient's condition, it will be reflected in the progress notes, but ward nurses may not always read those notes.
[N14, nurse/midwife, tertiary hospital]

Sustained visibility was therefore not only about displaying a current risk score but also about keeping previous risk information and newly detected changes visible throughout ongoing management.

Theme 3: Stakeholder Differences in Interpreting and Confirming Risk Information

Participants did not treat AI-generated risk information as self-evident. Before it could inform action, it would need to be checked against clinical judgment, women's own experience, or existing management processes. These routes of confirmation differed across stakeholder groups.

Women's Validation of AI-Generated Risk Information Through Clinical Advice and Bodily Experience

For pregnant women, AI-generated risk information functioned less as a final judgment than as a reference point to be checked against doctors' advice, offline examination results, and their own bodily condition. Several women noted that they would not make decisions based on the tool's result alone but would consider it together with their own judgment, clinical advice, and examination findings.

One pregnant woman stated directly that even if she used the tool, she would still keep her own judgment:

> *If I were the patient, I would still have my own judgment. For example, after using it, I would decide for myself. I wouldn't trust it completely.*
> *[P3, pregnant woman, 32 weeks]*

Another woman explained that when first encountering a tool like this, she would not readily believe the result, but would compare it with hospital examination findings:

> *The first time I used something like this, if it told me what was going on, I wouldn't believe it right away... I would still go to the hospital and see what the doctor said. If the hospital's result matched what the app recommended, then I would believe it later. What I worry about is that if they don't match, following it could delay things for me.*
> *[P16, postpartum woman]*

Another participant raised a similar concern, imagining the uncertainty that might arise if the AI result appeared very high risk while the doctor said there was no immediate problem and observation was enough:

> *For example, if the risk value was 90% and already very red, could it still happen that I go to the hospital and the doctor says it's fine, just go home and observe? Could that kind of situation still happen?*
> *[P4, pregnant woman, 28 weeks]*

Clinical Judgment Remained Central in the Use of AI-Generated Risk Information in Hospital Care

Hospital-based clinicians also did not treat AI-generated risk information as something that could be acted on independently of professional judgment. Participants described the tool as potentially convenient while emphasizing that AI-generated assessments still required clinicians' review and verification.

A nurse/midwife described the tool as convenient for doctors, while maintaining that "in the end, it still has to be based on the doctor's judgment" (N9, nurse/midwife, tertiary hospital). An obstetric doctor similarly described the system's assessment as preliminary and requiring verification:

> *The system could make an initial assessment, and then we would still check it ourselves, because we can't completely trust AI.*
> *[D9, obstetric doctor, tertiary hospital]*

In hospital care, AI-generated risk information was treated as support for clinical interpretation without replacing clinician judgment.

Reliance on Higher-Level Confirmation in Interpreting and Acting on Risk in Primary Care

In primary care, participants described risk interpretation and management as embedded in an existing process of initial screening, referral, and confirmation by higher-level hospitals. These practices shaped how participants considered the possible use of AI-based pregnancy risk assessment results in primary care.

One primary care doctor described this dependence clearly:

> *After initial risk screening, the referral form has to be sent immediately to a secondary-level or above hospital. They screen the woman again to see whether there are high-risk factors, and then we manage her according to their results.*
> *[D20, doctor, township health center]*

For primary care providers, locally identified risk could prompt referral or consultation, while higher-level confirmation informed subsequent risk classification and management.

This reliance on confirmation was shaped not only by existing referral procedures but also by the limits of primary-level providers' ability to interpret risk locally. One primary care doctor explained that conditions such as hyperthyroidism, heart disease, and blood disorders were difficult to judge at the primary level because staff encountered them infrequently and "only know a little" about some of these conditions (D22, doctor, central township health center). This boundary was even clearer at the village level. One village doctor described an upward consultation and feedback process:

> *We can consult higher-level providers about the situation... We can consult the township health center; if they are unsure, they consult the next level up and then get back to me.*
> *[D29, village doctor, village clinic]*

Another village doctor similarly described the need for higher-level support when problems could not be resolved locally:

> *When we encounter problems that we cannot resolve, we need help from doctors at higher-level hospitals... After all, we are at the village level, the lowest level.*
> *[D28, village doctor, village clinic]*

The anticipated use of AI-based pregnancy risk assessment results in primary care was understood in relation to existing pathways of referral, consultation, and higher-level confirmation.

Theme 4: Translating Risk Recognition Into Effective Management

Across stakeholder groups, participants expected AI-based pregnancy risk assessment results to support further action within existing care processes, although the emphasis differed by role: women focused on guidance for subsequent care decisions; primary health care professionals on referral, feedback, and continuity of follow-up; and hospital-based maternity care providers on clinical management and cross-level coordination.

From Risk Assessment to Clear Next-Step Guidance

For pregnant women, the usefulness of a risk result depended on whether it could tell them what required attention and what should be done next. A postpartum woman explained that a rough answer would not be enough if the system could not respond to her actual situation:

> *For example, if you ask a question, it will give you a rough answer... but after I further enter my actual situation, which item is abnormal? What should I pay attention to? It should be able to answer more specifically.*
> *[P1, postpartum woman]*

Health care professionals described a similar need for risk information to be linked with practical guidance. A county-level head nurse referred to existing pregnancy management applications that provide staged reminders and health prompts and felt that a comparable reminder function for staff would make the tool more useful:

> *If it could also actively remind health care professionals, I think this software would better fit our needs in terms of function and practicality.*
> *[N28, head nurse, county-level hospital]*

From the perspective of hospital care, 1 tertiary hospital doctor described how prediction could inform concrete clinical action in severe cases:

> *For example, for a woman who is still at a relatively early gestational age but whose condition is very serious, and the family still wants to continue the pregnancy, while the situation is actually getting worse, if the software could predict that continuing the pregnancy would do more harm than good, we would take corresponding measures and suggest early delivery. That would make the software quite meaningful.*
> *[D13, doctor, tertiary hospital]*

In primary care, next-step guidance was described as part of routine maternal health work. A community nurse described primary care work as extending from pregnancy registration through 42 days postpartum:

> *From the time a pregnant woman establishes her record here until 42 days postpartum, all of that is part of our work... We have to ensure the health of pregnant and postpartum women... we have to provide health education and reminders to her.*
> *[N27, nurse, community health service center]*

Both women and health care professionals expected risk assessment to lead to specific advice rather than stop at classification.

Risk Recognition Carried Forward Through Referral, Feedback, and Follow-Up

Once risk had been identified, the next concern was whether women could be kept within the follow-up pathway. In township and village settings, follow-up was described as a practical chain of notification, checking, reminding, and reporting back. One village doctor explained that when higher-level staff identified women requiring follow-up, "they notify us" and village doctors then completed visits and "give feedback by phone" (D28, village doctor, village clinic). Another village doctor described how follow-up continued when women did not attend recommended care: after feedback was received, "we go to her home again to explain" and advise further examination at a higher-level facility (D29, village doctor, village clinic).

County-level participants also described risk management as a continuing process rather than a single assessment event. A county-level obstetrician explained that staff used an existing system to identify high-risk women who had not recently attended antenatal care and then contacted them about the examinations they needed:

> *Nursing staff look in the Yunkang Huigu system to see whether a high-risk pregnant woman with high-risk factors has had antenatal care recently. If she hasn't, they will definitely call her and tell her what examination she needs to come for.*
> *[D24, obstetric doctor, county-level hospital]*

Follow-up was expected to remain connected to women's risk status and examination needs, rather than end with risk identification alone.

For women identified as higher risk, follow-up could also become a formalized management process. A county-level tertiary hospital doctor described how orange- and red-level cases were placed under case management after being rated as high risk:

> *For high-risk cases, the outpatient department keeps a high-risk record. For example, orange and red cases are all under case management, and each has its own file. Once rated as high risk, they are followed up regularly.*
> *[D26, obstetric doctor, county-level tertiary hospital]*

Cross-Level Information Transfer and Coordinated Decision-Making

For health care professionals, pregnancy risk management could involve consultation with senior colleagues within a facility as well as referral across institutions. A county-level obstetrician described how the decision to admit or refer a high-risk woman depended on consultation with a senior doctor rather than on an isolated judgment:

> *If I encounter a high-risk patient when admitting her, I report to my senior doctor. If the senior doctor says it is fine for the patient to stay here, then I admit her. If the senior doctor says the risk is too high, then we still recommend referral... If the risk is too high, then we transfer her out.*
> *[D27, obstetric doctor, county-level hospital]*

The same concern appeared in discussions of digital screening. A county-level nurse worried that risk information entered through a mini-program might not reach a higher-level hospital, disrupting continuity of care:

> *If we do pregnancy risk screening on this mini-program, could there be situations where the higher-level hospital cannot receive the woman's information? Because maternal management is now very strict, so what we worry about most is exactly this situation. We report it, but the higher-level hospital does not receive it. That kind of situation would count as ineffective management.*
> *[N30, nurse, county-level hospital]*

At the tertiary level, cross-level coordination was also described in relation to existing referral and consultation practices. A tertiary hospital doctor explained that lower-level hospitals could request consultation when a woman was in a relatively critical condition:

> *If the patient is relatively critical, the lower-level hospital will directly send a consultation request to the director, and they will notify the second-line doctor or the senior doctor on duty to consult on the case and decide whether she needs to be transferred to our hospital.*
> *[D6, obstetric doctor, tertiary hospital]*

The expected value of the tool was therefore tied to whether information could reach the right level of care in time and support coordinated judgment.

Automatic Identification and Reminders to Support Everyday Risk Management

Health care professionals valued automation mainly for its practical use in routine work. Automated classification or result generation could reduce repeated manual matching and save time, while reminders could help staff keep track of scheduled care and what needed to be done next. These accounts concerned automated classification and workflow support; the described functions did not in themselves require AI.

A tertiary hospital doctor expected the system to identify a woman's risk category automatically after relevant items had been selected or entered:

> *For example, if it could automatically identify what category of pregnant woman she belongs to based on my scoring, then we could just tick electronic boxes, and in the end it would automatically identify what type of pregnant woman she is. That would help us obtain results faster in clinical work.*
> *[D12, obstetric doctor, tertiary hospital]*

She added that this would help "avoid having to match things one by one, and reduce our workload" (D12, obstetric doctor, tertiary hospital).

Other tertiary hospital doctors described related forms of automation involving information integration, automatic matching, and reminders. One doctor emphasized that this would be useful only if the system could draw on information already generated in care:

> *Unless your app can connect with the patient's medical records, examinations, lab tests, and basic information such as vital signs, blood pressure, age, and weight, and match these automatically... after it is linked with the risk assessment form, the system reminds doctors.*
> *[D10, obstetric doctor, tertiary hospital]*

Another doctor felt that digitizing the assessment form, using keyword search, highlighting key items, and automatically generating results "would definitely be helpful and could save clinical time" (D7, obstetric doctor, tertiary hospital).

Reminders were valued as a way to reduce reliance on manual checking and tracking. A primary care nurse described the need for reminders when women were due for antenatal care:

> *It would be better if the system could give reminders—for example, when a pregnant woman is due for an antenatal check-up. Right now, we have to go through all the pregnant women ourselves. Every day, we have to open their records one by one to see whether it's time for their check-up, and then call them to follow up. If the system could directly remind us when someone is due for a check-up, we probably wouldn't miss anyone, or have someone reach her check-up date without coming in. Right now, it all depends on us checking manually, and with hundreds of pregnant women, it's hard not to miss someone.*
> *[N21, nurse, township health center]*

A village doctor described a similar expectation for everyday management at the village level:

If there were a WeChat mini-program, after the information was entered, we could see the basic management situation, and it could prompt us what should be done next. I think that would be necessary.
[D30, village doctor, village clinic]

Theme 5: Emotional Burden, Workload, and Conditions of Use Shaped Willingness to Use the Tool

Participants did not assume that an AI-based pregnancy risk assessment and management tool would be acceptable simply because it could identify risk. Willingness to use the tool depended on how risk prompts affected women emotionally, whether the tool reduced or increased clinical workload, and whether it could be incorporated into existing care in ways that users considered workable and acceptable.

Risk Prompts as Both Support for Timely Action and a Source of Anxiety

Pregnant women described risk prompts in ambivalent terms. While a warning could increase vigilance and prompt further assessment, an alarming result could also cause anxiety, particularly if it appeared inconsistent with a doctor's assessment.

One woman imagined a mismatch between an app-based warning and a doctor's assessment:

Could it also happen that I go to the hospital and the doctor says it's fine, just go home and observe? Could that kind of thing also happen? Sometimes I feel like I'd better not look at these apps; they're a bit scary. Things like that can cause anxiety.
[P4, pregnant woman, 28 weeks]

Not all participants regarded emotional burden as a reason to avoid risk information. A pregnant woman with a twin pregnancy said she would still want to view a risk result because it might prompt further examination and preventive action:

It would put some pressure on me, but at least I could try to prevent it... I'd still be willing to look at it. Even if it felt like a burden, after seeing it, I could at least go and get checked, and at least avoid that risk.
[P31, pregnant woman, 36 weeks, twin pregnancy]

A tertiary hospital nurse also emphasized the importance of guiding women into regular care after a risk was identified:

Even if there is pregnancy-related risk, regular and standard care can still control that risk very effectively. The point is to guide her to come in regularly, and then the risk can be controlled.
[N11, nurse, tertiary hospital]

The way risk assessment results were presented also mattered. One pregnant woman said, "I think one thing is very important: try not to create anxiety." She added that, from a professional perspective, the information should be made "a bit more objective" (P5, pregnant woman, 37 weeks). Taken together, these accounts suggest that risk prompts could be useful when they encouraged further assessment, regular care, or precautionary action, but could also increase anxiety when women were uncertain how to interpret the result.

Balancing Anticipated Workload Reduction Against Additional Operational Demands

For health care professionals, willingness to use the tool was closely tied to workload and workflow fit. Participants did not reject AI-based assessment in principle; rather, they assessed whether the tool would reduce repeated checking, manual data entry, and repeated updating or whether it would add another task to already busy clinical work.

The conditional nature of this willingness was clear in one nurse/midwife's account. When imagining a tool that was inconvenient and required additional assessment work, she said:

If it isn't convenient, and it adds to my workload, then I definitely won't want to use it. The delivery room is already busy, and if you ask me to assess people one by one, I probably won't do it.
[N16, nurse/midwife, tertiary hospital]

Yet the same participant described the tool as necessary when it could reduce record searching and make information more accessible at the bedside:

It's necessary, definitely necessary. First, it reduces our workload. We could see things at a glance, and we wouldn't have to keep looking through the records... If I can stand by her bedside one-to-one, that would be much better. It would definitely reduce part of the burden.
[N16, nurse/midwife, tertiary hospital]

A tertiary hospital nurse made a similar point in relation to routine documentation:

There's one precondition: it has to be simple and not increase our workload. If it can reduce the number of forms we have to fill in on the computer, then of course people would be willing to use it... If it can reduce workload, everyone will be willing. What people working in the clinic dislike most is having more work added when we're already busy.
[N17, nurse, tertiary hospital]

This concern extended to inpatient care, where repeated updating could itself become burdensome after admission. A nurse/midwife explained:

Yes, in the inpatient setting I wouldn't really want to use it. The main reason is that it has to keep being updated. Once a woman is admitted, we would have to keep updating the assessment during her stay. Doctors do ward rounds every morning, and our patients are not going to open the mini-program every day and wait for the doctors to look at it.
[N9, nurse/midwife, tertiary hospital]

When the tool was imagined as reducing work rather than adding steps, participants described it more positively. A primary-level nurse/midwife said that integrated antenatal information would "definitely make a big difference, because it would reduce a lot of workload" (N26, nurse/midwife, community health service center). Across these accounts, workload reduction was closely tied to whether information already available in routine care could be reused, rather than repeatedly searched for, entered, or updated through an additional process. Workload was not a secondary implementation issue; it shaped whether health care professionals regarded the tool as usable in the first place.

Making AI-Based Assessment Understandable, Trustworthy, and Workable in Practice

Participants anticipated that use of the proposed tool would depend on whether it was understandable, trustworthy, and workable in everyday care. For women, this included understanding why it mattered to their care, trusting the channel through which it was introduced, feeling confident that their privacy would be protected, and being able to enter the information it requested. Health care professionals also considered whether organizational rules and support would allow them to use it in routine work.

A tertiary hospital nurse regarded women's active participation as one of the strengths of the app:

The best thing about this app is that pregnant women can participate actively—that's the best part.

However, she also identified a potential barrier:

The problem is that if you ask pregnant women to do it, they may feel that this has nothing to do with them—that it's the doctor's job.
[N10, nurse, tertiary hospital]

She therefore emphasized the need to explain the purpose of the system early in antenatal care:

That could work. At the first antenatal visit, you would need to explain the importance of this system to her.
[N10, nurse, tertiary hospital]

Organizational arrangements could also support or obstruct use. The same nurse noted that implementation would require policy-level support and guidance: "When it comes to actually implementing it, people still feel that policy support and guidance are needed" (N10, nurse, tertiary hospital). Participants also identified training as a practical requirement for health care professionals expected to use the tool. A village doctor said, "We'd need some training. Without it, we wouldn't know how to use it" (D28, village doctor, village clinic). A nurse/midwife described a more immediate contradiction in the workplace:

The main problem is that we're not even allowed to use our phones at work, but at the same time you want to keep reminding us to check the phone all the time. That's a contradiction.
[N9, nurse/midwife, tertiary hospital]

Women also linked willingness to use the tool to the credibility of the channel through which it was introduced and to how their personal information would be protected. One postpartum woman said:

If a hospital recommended it, I'd trust it more. If it was an app from a hospital, it would also feel more professional and authoritative.
[P8, postpartum woman]

Another woman emphasized privacy protection:

One suggestion is that personal privacy must be protected. I think that is very important.
[P11, pregnant woman, 38 weeks]

Another concern was manual data entry, including whether women could understand the indicators and units they were asked to enter. One pregnant woman suggested that scanning and automatic extraction would be preferable to manual entry:

Don't make her enter everything herself. It would be better if you could scan the sheet and extract the information directly... Because if she has to enter it herself, you have to think about women with different levels of education... Some of them may not even understand the indicators, and they may not understand the units either.
[P5, pregnant woman, 37 weeks]

For women, reducing manual input was therefore not only a matter of convenience; it could also reduce the need to interpret clinical indicators and units that some might not understand.

Participants anticipated that continued use would require more than access to a digital tool. Women would need to see its relevance, trust how it was introduced, feel confident that their privacy would be protected, and be able to enter the information it requested; health care staff would need organizational support to use it in routine care.

Discussion

Principal Findings

This qualitative descriptive study examined expectations and perceived implementation concerns regarding AI-based pregnancy risk assessment in maternity care based on participants' discussion of standardized conceptual material rather than on experience with an operational AI system. Across stakeholder groups, AI-generated pregnancy risk estimates were not regarded as self-explanatory or sufficient to guide action on their own. Participants expected model-generated risk outputs to be understood in relation to other pregnancy and clinical information and to inform subsequent care within existing maternity risk-management processes. However, what was needed for such estimates to become meaningful and actionable differed by stakeholder role. Pregnant and postpartum women emphasized understandable risk information and support for subsequent care decisions; primary health care professionals focused on referral, higher-level confirmation, feedback, and continuity of follow-up; and hospital-based maternity care providers emphasized interpretation alongside clinical information, professional judgment, and coordination across levels of care. Participants also expected risk assessment to be updated as pregnancy-related information and risk changed over time. At the same time, willingness to use the tool was shaped by whether risk prompts supported action without causing unnecessary anxiety for women and whether the tool reduced rather than added to health care professionals' workload.

Interpretation of Findings

The interviews suggest that a future AI-generated risk estimate could have different practical implications across stakeholder roles. Women tended to make sense of a risk result by comparing it with their own bodily sensations, examination findings, and health care professionals' advice. Hospital-based maternity care providers emphasized that risk assessment results should be considered alongside clinical evidence and professional judgment, whereas primary health care professionals were more concerned with higher-level confirmation and what action should follow. Previous perinatal AI studies have similarly shown that patients want opportunities to discuss predictive results with health care professionals [12,13], while obstetric clinicians have emphasized retaining professional authority to judge whether an AI-supported assessment is sufficiently reliable to inform care [11].

These differences were closely related to stakeholders' positions and responsibilities within the maternity care pathway. The AI-generated risk estimates could therefore serve different practical purposes: helping women make sense of their risk and determine an appropriate course of action, prompting further assessment or referral in primary care, or providing additional information for clinical judgment in hospital care. Their usefulness was consequently not determined by the prediction alone but also by whether the recipient had the information, authority, and route to action needed to use it. This suggests that interpretability in AI-based pregnancy risk assessment involves not only presenting the risk estimate clearly but also making its clinical and practical meaning clear to the person expected to act on it. Broader clinical AI research has highlighted the importance of differing stakeholder perspectives for implementation [6]; our findings show how such differences may operate around the same risk outputs within a maternity risk-management pathway.

The practical meaning of an AI-generated risk estimate depended on the processes that followed its generation. Primary health care professionals described their role in pregnancy risk management in terms of initial screening, referral, higher-level confirmation, feedback, and continued follow-up. Their concern was therefore not only whether AI could identify risk but who would confirm an AI-generated result and on what basis subsequent management should proceed. Hospital-based providers raised a related issue from a different position: AI-generated risk information could support assessment, but clinical judgment remained central to deciding what the result meant for the woman's current care. These findings suggest that introducing AI-based risk assessment into maternity care would require a clear place for an AI-generated risk estimate within existing processes of confirmation, clinical assessment, referral, and follow-up. This is particularly relevant in China, where national guidance already defines responsibilities for risk screening, assessment and classification, referral, feedback, follow-up, and reassessment across levels of care [14,15].

How the AI estimate enters this pathway matters in practical terms. Participants valued cross-level information transfer when it supported coordinated management, and automated identification when it reduced repeated searching and manual work. A provincial maternal and child health information system in Inner Mongolia provides an example of how 5-color pregnancy risk management and cross-institutional information exchange can already be supported digitally [5]. Participants' references to existing risk classifications and digital systems illustrate the clinical and organizational arrangements through which they understood the potential role of AI-based pregnancy risk assessment. In this context, AI-based risk estimation concerned the generation of pregnancy-related risk estimates, whereas information exchange, reminders, referral, and follow-up formed part of the broader care processes and digital functions surrounding the use of these estimates.

Reviews of pregnancy-related ML and AI decision support systems nevertheless show that movement from model development to routine clinical use remains limited [2,3], while broader clinical AI research has identified workflow fit and interoperability as important implementation concerns [6]. In this context, the challenge is not simply to add an AI prediction to an existing system, but to incorporate the result into processes of review and action without creating additional work alongside existing care processes. As participants also described pregnancy risk as changing over time, such use would need to allow reassessment as new

information emerged rather than treat the AI result as a one-time output.

The potential benefits of AI-based risk prediction could be accompanied by new burdens for those expected to respond to it. Women valued earlier warning and guidance, but some anticipated greater anxiety when a high-risk result was not accompanied by sufficient explanation or a clear next step. Similar concerns were reported by Benda et al [13], whose participants highlighted concerns about the emotional impact of high-risk AI predictions and emphasized that predictive AI should provide actionable benefits while minimizing anxiety. For women in our study, the value of earlier risk information therefore depended partly on whether it helped them understand what the result meant and what action was required, rather than simply alerting them to risk.

For health care professionals, workload and operational burden were recurring concerns, although the salience of these concerns may have been partly shaped by the wording of one interview-guide prompt ("without adding excessive burden"). Participants described additional data entry, repeated checking, or extra operational steps as potentially making the tool difficult to sustain in routine work. A recent systematic review found that the effect of clinical AI on workload varied by application and that evidence for imaging AI and clinical decision support remained very uncertain [31]. In pregnancy risk assessment, the practical benefit of earlier or more automated risk recognition may therefore depend partly on what is required after a prediction is produced. A tool that identifies risk more efficiently but requires substantial additional effort to interpret or act on its output may shift rather than reduce work. The value of AI-based risk assessment therefore needs to be considered in relation not only to the benefits of prediction but also to the burden placed on those expected to respond to it.

Limitations

The multistakeholder, multilevel sample allowed comparison across roles and care settings, but several limitations should be considered. First, participants discussed the prospective use of AI-based pregnancy risk assessment after viewing standardized stimulus material rather than interacting with an implemented system; some function-specific responses may therefore have been shaped by features included in the stimulus. One interview-guide prompt also used the phrase "without adding excessive burden," which may have foregrounded workload as an implementation concern and needs to be considered when interpreting these findings. Second, recruitment and interviewing occurred in 3 phases from August 2024 to May 2026. Participants' familiarity with AI and digital health may have changed over this period, but the study was not designed to examine temporal change. Third, the study was conducted in 1 Chinese province, so referral, follow-up, and professional responsibilities may differ elsewhere. Participant validation of the final analytic findings was not undertaken. Finally, the study did not evaluate a specific algorithm, interface, or implementation strategy, and issues such as privacy, consent, cybersecurity, interoperability, and data standards were not examined comprehensively. These issues should be addressed when an operational system is developed and tested.

Conclusions

The findings suggest that the potential value of AI-based pregnancy risk assessment may depend on whether model-generated risk estimates can be meaningfully interpreted by different users and incorporated into existing maternity risk management processes. Future development should clarify how such estimates relate to existing pregnancy risk classification and clinical assessment, as well as how they connect with referral, feedback, follow-up, and responsibilities across levels of maternity care, without adding unnecessary workload or operational demands. As this study examined expectations toward a proposed rather than implemented tool, prospective evaluation is needed to determine how these issues manifest in prototype testing and real-world use, including usability, workflow fit, and how AI-generated risk estimates are interpreted and acted on in practice.

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Generative AI Use

The authors used ChatGPT (OpenAI) to support the manuscript preparation and revision process. Specifically, it was used for English-language refinement, including refinement of the English translations of selected deidentified participant quotations, and consistency checking between the responses to reviewers and the revised manuscript. The quotations were selected and translated by the authors before AI-assisted editing; no full transcripts, complete interview records, or identifiable participant information were entered into ChatGPT. All AI-assisted outputs were critically reviewed by the authors, who applied independent judgment and, where relevant, checked suggestions against the original data before incorporating any changes. Generative AI was not used to conduct interviews, transcribe data, perform primary coding, or make final analytic decisions. Responsibility for the final manuscript lies entirely with the authors.

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design; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to submit the article for publication.

Data Availability

The datasets generated and analyzed during the study are available from the corresponding author on reasonable request.

Authors' Contributions

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Writing – original draft: Z Luo
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All authors reviewed and approved the final manuscript and agreed to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Interview guide.
[DOC File (Microsoft Word File), 21 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Standardized stimulus material shown to participants: original Chinese version and English translation.
[PPTX File (Microsoft PowerPoint File), 455 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Illustrative examples of the analytic progression from meaning units to descriptive themes.
[DOC File (Microsoft Word File), 32 KB-Multimedia Appendix 3]

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Abbreviations

ML: machine learning

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