Journal of Clinical and Nursing Research, 2026, Volume 10, Issue 6
http://ojs.bbwpublisher.com/index.php/JCNR
Online ISSN: 2208-3693
Print ISSN: 2208-3685

Clinical Applications of AI-Based Fetal Monitoring in Labor Management and Its Impact on Maternal and Neonatal Outcomes

Yeqing Su

Department of Obstetrics, Affiliated Hospital of Hebei University, Baoding 071000, Hebei, China

Abstract: *Objective*: To investigate the clinical application of AI-based labor monitoring in labor management and its impact on maternal and fetal outcomes. *Methods*: A total of 240 pregnant women scheduled for vaginal trial of labor admitted to our hospital from January 2024 to June 2025 were selected as study subjects. They were randomly divided into a control group and an observation group, each comprising 120 cases. The control group underwent traditional manual timed monitoring, while the observation group received AI-based labor monitoring. This study compared the duration of each stage of labor, mode of delivery, incidence of related complications, and rate of neonatal adverse events between the two groups, and evaluated the accuracy of identifying abnormal labor patterns and differences in healthcare workload. *Results*: The duration of the first and second stages of labor, as well as the total duration of labor, was significantly shorter in the observation group than in the control group; the incidence of cesarean sections without medical indications, postpartum hemorrhage, and puerperal infections was significantly lower in the observation group than in the control group ($p < 0.05$); the incidence of meconium-stained amniotic fluid, mild asphyxia, and neonatal intensive care unit admission rates were all lower in the observation group than in the control group ($p < 0.05$); the observation group had lower rates of missed or misdiagnosed labor abnormalities, and the workload associated with medical documentation and repetitive monitoring was significantly reduced ($p < 0.05$). *Conclusion*: The AI-based labor monitoring system enables comprehensive, continuous, and precise management throughout labor, effectively accelerating labor progression, avoiding overtreatment, and reducing the risk of adverse maternal and neonatal complications. It also optimizes obstetric workflows and enhances the standardization of diagnosis and treatment, demonstrating promising prospects for clinical implementation.

Keywords: Artificial intelligence; Labor monitoring; Labor management; Maternal and neonatal outcomes; Smart obstetrics; Precision medicine

Online publication: Jun 30, 2026

1. Introduction

Vaginal delivery is the primary method of natural childbirth; however, the labor process is dynamic and variable, with significant individual differences. The progression of labor is highly susceptible to interference from multiple factors, such as uterine contractions, the birth canal, fetal position, fetal condition, and the mother's psychological state. This can easily lead to labor abnormalities and intrauterine hypoxia. If not promptly identified and effectively intervened upon, it can readily trigger adverse events such as labor arrest, dystocia, postpartum hemorrhage, and neonatal hypoxic injury. Therefore, it is essential to establish a precise, continuous, and efficient labor monitoring system to achieve the goals of reducing perinatal risks and improving birth outcomes [1].

Traditional labor management models rely heavily on healthcare providers conducting scheduled physical examinations, intermittent data recording, and experience-based interpretation. These approaches suffer from inherent flaws, including fixed monitoring intervals, fragmented data, delayed recording, and significant subjective bias. Furthermore, influenced by factors such as staffing levels, night shifts, and work fatigue, manual monitoring is highly prone to missing or misinterpreting early abnormalities, which can lead to delayed or excessive interventions, resulting in prolonged labor and an increase in unnecessary cesarean sections [2]. As the digital transformation of smart healthcare continues to advance, technologies such as artificial intelligence, deep learning, multi-source data fusion, and intelligent risk prediction are gradually being integrated into obstetric clinical practice. Artificial intelligence-based labor monitoring systems can automatically capture multidimensional data, including uterine contraction patterns, fetal heart rate dynamics, cervical dilation, descent of the presenting part, and maternal vital signs, and use algorithmic models to perform real-time analysis, tiered alerts, and trend forecasting, effectively addressing the shortcomings of manual monitoring [3]. This study employs a prospective controlled design to systematically analyze the advantages of intelligent labor monitoring, providing a practical basis for establishing standardized, precise, and efficient smart labor management models in clinical practice.

2. Materials and methods

2.1. General information

A total of 240 full-term pregnant women scheduled for vaginal delivery at our hospital's obstetrics department between January 2024 and June 2025 were selected as study subjects and randomly divided into a control group and an observation group, each comprising 120 cases. The observation group consisted of women aged 22–35 years (mean 28.63 ± 3.12 years) with a gestational age of 39.25 ± 1.06 weeks; it included 98 primiparous women and 22 multiparous women; The control group ranged in age from 21 to 36 years, with a mean age of (28.41 ± 3.25) years and a gestational age of 39.18 ± 1.12 weeks; it included 96 primiparous women and 24 multiparous women. There were no statistically significant differences between the two groups in baseline age, gestational age, parity, or general physical condition ($p > 0.05$), and the groups were comparable.

2.1.1. Inclusion criteria

(1) Gestational age 37–42 weeks;

(2) Singleton pregnancy, cephalic presentation;

(3) Normal pelvic anatomy and eligibility for trial of labor;

(4) Normal cognitive function and ability to cooperate with continuous monitoring;

(5) Complete clinical records

2.1.2. Exclusion criteria

(1) Cesarean scar, abnormal fetal presentation, or cephalopelvic disproportion;
(2) High-risk pregnancies, including severe gestational hypertension, gestational diabetes, or placenta previa;
(3) Severe underlying cardiac, hepatic, or renal disease; fetal growth restriction or intrauterine malformations;
(4) Cases where trial labor was discontinued, patients were transferred to another hospital, or data were missing.

2.2. Study methods

2.2.1. Control group

Conventional labor management was employed. Medical staff conducted intermittent labor monitoring in accordance with obstetric clinical guidelines, regularly monitoring the intensity of uterine contractions, fetal heart rate, cervical dilation, and descent of the presenting part. They manually recorded labor progress, plotted labor curves, interpreted fetal heart rate monitoring tracings, and assessed labor progression based on clinical experience. Conventional symptomatic management was provided for abnormal labor conditions.

2.2.2. Observation group

In addition to routine obstetric care, an artificial intelligence-based labor monitoring system was used throughout the entire process to implement intelligent labor management.

(1) Continuous data collection was conducted around the clock; the system automatically and synchronously captured key indicators such as fetal heart rate dynamics, uterine contraction parameters, and maternal vital signs, enabling uninterrupted monitoring and eliminating blind spots and recording errors associated with manual monitoring intervals.
(2) Leveraging deep learning algorithms, the system performs intelligent analysis of fetal heart rate variability, uterine contraction rhythm consistency, and labor progression speed. It issues tiered alerts for abnormal conditions such as labor arrest, prolonged latent phase, and early fetal intrauterine hypoxia, prompting immediate clinical intervention.
(3) The system automatically generates dynamic labor progress curves and, by integrating the mother's individual baseline data, intelligently predicts labor trends to provide personalized guidance on the optimal timing for intervention.
(4) The system pushes standardized management protocols for various abnormal scenarios, unifies clinical intervention procedures, and reduces variability in subjective diagnosis and treatment. It also automatically archives data throughout the process, ensuring the delivery process is traceable and reviewable.

Medical staff combine intelligent alerts with clinical experience to implement comprehensive interventions, ensuring precise and standardized labor management.

2.3. Observation indicators

(1) Duration of labor

Calculate and compare the durations of the first, second, and third stages of labor, as well as the total duration of labor, between the two groups;

(2) Maternal outcomes

Record the incidence of cesarean sections, non-emergency cesarean sections, postpartum hemorrhage, puerperal infections, and cervical lacerations in both groups;

(3) Neonatal outcomes

Compare the incidence rates of meconium-stained amniotic fluid, mild neonatal asphyxia, and NICU admission;

(4) Quality of care and workload

Calculate the incidence of missed or misdiagnosed labor abnormalities; compare differences in the time spent on routine documentation and the workload associated with repetitive monitoring between the two groups.

2.4. Statistical methods

Data were analyzed using SPSS 26.0 statistical software. Continuous variables are expressed as mean ± standard deviation, and intergroup comparisons were performed using the independent samples *t*-test. Categorical variables are presented as counts and percentages, and the chi-square χ^2 test was used. A *p*-value < 0.05 was considered statistically significant.

3. Results

3.1. Comparison of labor duration between the two groups

Statistical results showed that the duration of the first stage, second stage, and total labor in the observation group was significantly shorter than that in the control group, with statistically significant differences between groups ($p < 0.05$); there was no significant difference in the duration of the third stage between the two groups ($p > 0.05$). See **Table 1** for details.

Table 1. Comparison of labor duration at each stage between the two groups ($\bar{x} \pm s$)

Group	First stage of labor	Second stage	Third stage of labor	Total labor
Observation group (n = 120)	426.35 ± 52.16	45.28 ± 10.36	6.85 ± 2.12	478.48 ± 56.32
Control group (n = 120)	512.68 ± 63.42	58.76 ± 12.15	7.12 ± 2.35	578.56 ± 68.45
t	11.517	9.248	0.935	12.368
p	< 0.001	< 0.001	0.351	< 0.001

3.2. Comparison of maternal delivery outcomes between the two groups

The overall cesarean section rate, the rate of cesarean sections without medical indication, and the incidence of postpartum hemorrhage and puerperal infection were all lower in the observation group than in the control group, with statistically significant differences ($p < 0.05$); the incidence of cervical lacerations was similar between the two groups, with no statistically significant difference ($p > 0.05$). See **Table 2** for details.

Table 2. Comparison of adverse maternal delivery outcomes between the two groups [n (%)]

Group	Cesarean section rate	Unindicated cesarean section rate	Postpartum hemorrhage	Puerperal infection	Cervical laceration
Observation group (n = 120)	12 (10.00)	4 (3.33)	3 (2.50)	2 (1.67)	5 (4.17)
Control group (n = 120)	25 (20.83)	13 (10.83)	10 (8.33)	8 (6.67)	7 (5.83)
χ^2	5.684	5.217	4.072	3.968	0.357
p	< 0.05	< 0.05	< 0.05	< 0.05	> 0.05

3.3. Comparison of neonatal outcomes between the two groups

The incidence of meconium-stained amniotic fluid, mild asphyxia, and NICU admission was significantly lower in the observation group than in the control group ($p < 0.05$); no cases of severe neonatal asphyxia were observed in either group. See **Table 3** for details.

Table 3. Comparison of neonatal outcomes between the two groups [n (%)]

Group	Meconium-stained amniotic fluid	Mild neonatal asphyxia	NICU admission rate
Observation group (n = 120)	6 (5.00)	2 (1.67)	3 (2.50)
Control group (n = 120)	15 (12.50)	9 (7.50)	11 (9.17)
χ^2	4.227	4.669	4.855
p	0.039	0.031	<0.028

3.4. Comparison of clinical quality and workload between the two groups

The observation group showed significantly lower rates of missed and misdiagnosed abnormal labor, significantly reduced time spent on routine documentation by medical staff, and a substantial decrease in repetitive workload; all differences between groups were statistically significant ($p < 0.05$). See **Table 4** for details.

Table 4. Comparison of clinical quality and workload between the two groups

Group	Rate of missed diagnosis of abnormal labor [n(%)]	Misdiagnosis rate of abnormal labor [n(%)]	Average daily documentation time ($\bar{x} \pm s$)
Observation group (n = 120)	1 (0.83)	2 (1.67)	2.15 ± 0.42
Control group (n = 120)	8 (6.67)	9 (7.50)	3.86 ± 0.65
$/t$	4.733	4.669	24.205
p-value	0.029	0.031	< 0.001

4. Discussion

In the safe management of vaginal delivery, the timely implementation of accurate and effective labor monitoring is a crucial measure for ensuring safe maternal and neonatal outcomes [4]. In the past, due to limited information technology, obstetric healthcare providers primarily relied on manual monitoring for women undergoing vaginal delivery. However, this method, which involved scheduled physical examinations and subjective interpretation, suffered from shortcomings such as sporadic monitoring points and delayed data updates. Consequently, it was difficult to capture subtle changes in labor dynamics, making it highly likely to delay intervention in the event of early abnormalities and hindering obstetric quality control [5].

With the continuous advancement of information technology, artificial intelligence (AI) labor monitoring systems, which leverage big data algorithms and real-time dynamic analysis capabilities, have been widely adopted in obstetric care, marking a breakthrough over traditional manual monitoring [6,7]. By integrating AI labor monitoring technology into labor management practices, this study found that its clinical application can significantly shorten the duration of labor, The analysis suggests that by continuously capturing dynamic fluctuations in uterine contraction patterns, fetal heart rate changes, and the rate of labor progression, the AI monitoring system can provide early warnings for issues such as labor failure, delayed progression, and early depletion of intrauterine reserve. This alerts healthcare providers to promptly implement targeted interventions, such as positional adjustments and oxytocin adjustments, thereby correcting abnormal labor and accelerating the natural delivery process [8]. This study also found that, compared to the control group, the observation group showed significantly lower overall cesarean section rates, rates of unindicated cesarean sections, and incidence of postpartum hemorrhage and puerperal infections ($p < 0.05$). The core mechanism lies in the fact that AI algorithms, trained on massive amounts of clinical data, can accurately distinguish between normal fluctuations and genuine intrauterine abnormalities, thereby maximizing improvements in maternal delivery outcomes; Regarding neonatal prognosis, labor management utilizing AI-based delivery monitoring technology can dynamically monitor the physiological status of pregnant women and newborns through intelligent systems, rapidly identify early signs of hypoxia, and buy time for healthcare providers to initiate emergency interventions, thereby reducing the risk of neonatal hypoxia, asphyxia, and admission to intensive care units [9]. From a hospital management perspective, AI monitoring technology uses relevant equipment and sensors to collect labor data, perform timely intelligent analysis, and archive records with a single click. This significantly simplifies administrative tasks for medical staff and alleviates their workload. At the same time, the AI system's standardized algorithm-based interpretation capabilities unify diagnostic and treatment standards, avoiding the diagnostic biases associated with reliance on individual experience, thereby effectively enhancing the standardization and consistency of labor management [10].

5. Conclusion

In summary, clinical labor management based on AI-driven delivery monitoring technology is an inevitable requirement for meeting the high standards of maternal and infant safety in the new era. By applying intelligent systems and AI algorithms, it enables dynamic, precise, controllable, and standardized fine-grained management throughout the entire delivery process. This significantly shortens the duration of labor, reduces excessive medical interventions, and lowers the incidence of maternal and infant complications, fundamentally addressing the shortcomings and limitations of traditional manual monitoring models. At the same time, AI monitoring technology, through automated data collection and intelligent analysis of labor progress data, can significantly reduce the workload of medical staff, demonstrating high clinical value and promising prospects for widespread adoption.

Disclosure statement

The author declares no conflict of interest.

References

[1] Obstetrics Group of the Obstetrics and Gynecology Branch, Chinese Medical Association; Perinatal Medicine Branch, Chinese Medical Association, 2023, Guidelines for the Prevention and Management of Postpartum Hemorrhage (2023). Chinese Journal of Obstetrics and Gynecology, 58(6): 401–409.

[2] Hadad S, Oberman M, Arie A, et al., 2021, Intrapartum ultrasound at the initiation of the active second stage of labor predicts spontaneous vaginal delivery. Am J Obstet Gynecol MFM, 3(1): 100249.

[3] Zhang P, Zhang Y, Wang Q, et al., 2025, Intrapartum Ultrasound Indicators for Predicting the Difficulty of Vacuum Extraction. Chinese Journal of Perinatal Medicine, 28(3): 194–202.

[4] Huang Y, 2024, The Clinical Value of Real-time Ultrasound Monitoring in Labor Assessment and Delivery. Journal of Rare and Rare Diseases, 31(7): 99–101.

[5] Shang X, 2024, Application of Artificial Intelligence in Intrapartum Fetal Heart Rate Monitoring, thesis, Guangzhou Medical University.

[6] Wu Y, 2023, Establishment and Validation of a Predictive Model for Vaginal Delivery Success Rates Based on Real-World Data, thesis, Sichuan University.

[7] Oberman M, Avrahami I, Lavi S, et al., 2023, Assessment of Labor Progress by Ultrasound vs Manual Examination: A Randomized Controlled Trial. Am J Obstet Gynecol MFM, 5(2): 100817.

[8] Lu Y, Li Z, Bai J, et al., 2026, Application and Prospects of Artificial Intelligence in Full-Term Obstetric Management. Chinese Journal of Practical Gynecology and Obstetrics, 42(1): 124–128.

[9] Yu L, Wang H, Zhou Y, et al., 2025, The Value of an Obstetric Intelligent Assistant in Predicting Postpartum Hemorrhage in Vaginal Deliveries. Chinese Journal of Perinatal Medicine, 28(10): 829–834.

[10] Wang Z, 2025, Research and Application of Intelligent Algorithms for the Full Lifecycle Health Management of Pregnant Women and Mothers, thesis, Sichuan University.