# IOT-based wearable uterine contraction and fetal monitoring system with artificial intelligence for prevention of preterm labour and obstetric nursing management

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DOI: 10.5281/zenodo.21304679

## Abstract:

Preterm labour remains one of the leading causes of neonatal morbidity and mortality worldwide, accounting for significant healthcare expenditures and long-term developmental disabilities among surviving infants. Early identification of uterine activity and fetal compromise is essential for timely clinical intervention, yet conventional antenatal monitoring methods rely predominantly on intermittent hospital visits, limiting continuous surveillance of high-risk pregnancies. Recent advances in the Internet of Things (IoT), wearable biosensors, artificial intelligence (AI), cloud computing, and mobile health technologies have transformed maternal healthcare by enabling continuous, remote, and personalized monitoring throughout pregnancy. IoT-based wearable maternal monitoring systems integrate physiological sensors capable of measuring uterine contractions, fetal heart rate, maternal heart rate, body temperature, oxygen saturation, respiratory rate, and physical activity. These devices transmit real-time physiological data to cloud platforms, where AI algorithms analyse patterns to identify early indicators of preterm labour and fetal distress. Intelligent decision-support systems subsequently generate automated alerts for healthcare professionals and pregnant women, facilitating rapid clinical assessment and intervention.

Artificial intelligence techniques, including machine learning, deep learning, ensemble learning, and predictive analytics, significantly improve diagnostic accuracy by identifying subtle physiological changes that are difficult to recognize through conventional monitoring. Such technologies support individualized risk assessment, reduce unnecessary hospital admissions, optimize obstetric nursing management, and enhance maternal–fetal outcomes through continuous surveillance and timely clinical decision-making. Obstetric nurses play a pivotal role in implementing AI-assisted monitoring systems by interpreting alerts, educating patients, coordinating multidisciplinary care, and ensuring adherence to evidence-based interventions.

Despite promising clinical applications, challenges remain regarding sensor accuracy, cybersecurity, interoperability, ethical considerations, data privacy, and equitable access in low-resource settings. Continued technological innovation, rigorous clinical validation, and integration into routine obstetric practice are essential for maximizing the benefits of AI-enabled maternal monitoring systems. This article reviews the principles, technological components, clinical applications, nursing implications, benefits, challenges, and future prospects of IoT-based wearable uterine contraction and fetal monitoring systems for preventing preterm labour and improving obstetric nursing management.

## Keywords:

Artificial Intelligence; Internet of Things; Wearable Sensors; Preterm Labour; Fetal Monitoring; Obstetric Nursing; Maternal Health; Remote Patient Monitoring.

## 1. Introduction:

Pregnancy is a dynamic physiological process requiring continuous adaptation of maternal cardiovascular, endocrine, respiratory, and reproductive systems to support fetal growth and development. Although most pregnancies progress without significant complications, approximately one in every ten pregnancies worldwide is affected by preterm birth, defined as delivery before 37 completed weeks of gestation. Preterm birth remains one of the foremost challenges in maternal and neonatal healthcare because it substantially increases neonatal mortality, respiratory distress syndrome, intraventricular haemorrhage, sepsis, cerebral palsy, developmental delay, and lifelong disability[1].

One of the greatest clinical difficulties is that preterm labour often begins with subtle physiological changes that may remain unnoticed until cervical changes become irreversible. Early uterine contractions may resemble Braxton Hicks contractions, leading pregnant women to underestimate their clinical significance. Similarly, gradual alterations in fetal heart rate variability may occur long before overt fetal distress develops. Consequently, continuous maternal-fetal surveillance has emerged as a priority in modern obstetric practice.

Traditional prenatal monitoring primarily depends on scheduled antenatal visits during which maternal vital signs, fetal heart rate, uterine activity, and laboratory investigations are assessed intermittently. While these evaluations remain indispensable, they provide only a brief snapshot of maternal and fetal health. Physiological abnormalities developing between clinic visits may remain undetected, particularly among women residing in remote areas or those with limited access to specialized obstetric services.

Rapid technological advancements in digital healthcare have fundamentally transformed approaches to maternal monitoring. The convergence of wearable biosensors, Internet of Things (IoT) infrastructure, wireless communication, cloud computing, big data analytics, and artificial intelligence has enabled continuous remote monitoring of pregnant women within their home environment. Rather than relying solely on episodic hospital assessments, clinicians can now receive real-time physiological information throughout pregnancy, thereby facilitating earlier recognition of complications.

The Internet of Things refers to an interconnected network of physical devices embedded with sensors, communication modules, processors, and software capable of collecting, transmitting, and exchanging healthcare information through secure digital platforms. Within maternal healthcare, IoT technology allows wearable devices to monitor multiple physiological parameters continuously without restricting maternal mobility. These systems are increasingly designed as lightweight abdominal belts, smart garments, adhesive patches, wristbands, and wireless fetal monitoring devices that provide comfortable long-term monitoring.

Artificial intelligence further enhances the clinical utility of wearable monitoring by converting large volumes of physiological data into meaningful clinical information. Machine learning algorithms recognize hidden relationships among uterine contraction frequency, contraction intensity, fetal heart rate variability, maternal vital signs, physical activity, sleep quality, and biochemical risk factors. Instead of relying solely on fixed clinical thresholds, AI systems continuously learn from historical patient data to improve prediction accuracy and personalize risk assessment.

The integration of wearable sensors with AI-based predictive analytics supports the development of intelligent clinical decision-support systems capable of identifying early warning signs before severe maternal or fetal deterioration occurs. For example, increasing contraction frequency combined with abnormal fetal heart rate variability may trigger automated alerts recommending urgent obstetric evaluation. Such predictive systems provide clinicians with valuable opportunities to initiate interventions including hydration, corticosteroid administration, tocolytic therapy, cervical assessment, or transfer to tertiary healthcare facilities before preterm birth becomes inevitable.

Obstetric nurses occupy a central position within this technological transformation. Beyond traditional bedside responsibilities, modern obstetric nursing increasingly incorporates digital health competencies involving remote patient monitoring, interpretation of AI-generated alerts, patient education regarding wearable technologies, data documentation, telehealth consultation, and multidisciplinary communication. Nurses remain essential in ensuring appropriate clinical responses to automated alerts while preserving compassionate, patient-centred maternity care.

Several wearable maternal monitoring devices have already demonstrated promising clinical performance. Modern biosensors can continuously record uterine electromyography (EHG), fetal electrocardiography (fECG), maternal heart rate, oxygen saturation, respiratory rate, skin temperature, maternal posture, sleep patterns, and physical activity. Cloud-based software platforms aggregate these diverse physiological signals into comprehensive maternal health dashboards accessible to obstetricians, nurses, and healthcare institutions[1].

The application of artificial intelligence extends beyond simple monitoring. Predictive models using deep learning, convolutional neural networks, recurrent neural networks, support vector machines, random forests, gradient boosting algorithms, and ensemble learning techniques can classify pregnancy risk, predict preterm labour probability, detect fetal distress, and recommend individualized nursing interventions. Continuous algorithm refinement through large clinical datasets improves predictive performance while reducing false-positive alerts.

In addition to clinical benefits, IoT-enabled maternal monitoring offers important public health advantages. Remote monitoring decreases unnecessary hospital visits, reduces healthcare costs, improves access for rural populations, supports home-based antenatal care, minimizes travel-related burdens during high-risk pregnancy, and facilitates continuity of care during infectious disease outbreaks or healthcare workforce shortages.

Despite these advantages, widespread implementation requires careful consideration of technological reliability, data security, ethical governance, patient acceptance, interoperability between healthcare systems, and regulatory compliance. Clinical validation through multicentre trials remains essential before AI-driven maternal monitoring becomes a universal standard of obstetric practice.

The future of maternal healthcare is expected to involve increasingly intelligent, patient-centred ecosystems in which wearable sensors, artificial intelligence, cloud computing, electronic health records, and telemedicine function collaboratively to improve pregnancy outcomes. Such integrated digital health platforms have the potential to transform preterm labour prevention from reactive treatment to proactive prediction and prevention.

## 2. Global burden of preterm labour:

Preterm labour represents one of the most significant global public health challenges affecting maternal and neonatal health. According to international estimates, approximately 13–15 million babies are born prematurely each year, accounting for nearly one in every ten live births worldwide. Prematurity is currently recognized as the leading direct cause of neonatal mortality and a major contributor to under-five mortality, particularly in low- and middle-income countries where access to advanced neonatal intensive care is limited.

The burden of preterm birth extends far beyond the neonatal period. Survivors frequently experience lifelong complications including chronic respiratory disease, cerebral palsy, visual impairment, hearing loss, intellectual disability, behavioural disorders, poor academic achievement, and increased susceptibility to chronic non-communicable diseases later in life. These consequences impose substantial emotional, social, and economic burdens on families and healthcare systems.

The incidence of preterm labour varies considerably across geographical regions. Countries with limited maternal healthcare infrastructure, inadequate antenatal services, nutritional deficiencies, infectious diseases, poverty, and limited access to emergency obstetric care generally report higher preterm birth rates. Even in high-income countries, increasing maternal age, assisted reproductive technologies, obesity, diabetes mellitus, hypertension, and multiple pregnancies have contributed to persistent rates of prematurity.

Preterm labour results from a complex interaction of biological, environmental, genetic, behavioural, and socioeconomic factors. Major maternal risk factors include previous preterm birth, cervical insufficiency, uterine anomalies, multiple gestation, urinary tract infections, sexually transmitted infections, preeclampsia, chronic hypertension, diabetes mellitus, thyroid disorders, smoking, substance abuse, poor maternal nutrition, anemia, excessive physical workload, psychological stress, intimate partner violence, and inadequate prenatal care. In many pregnancies, however, spontaneous preterm labour develops without any clearly identifiable cause, emphasizing the need for continuous physiological monitoring capable of detecting early pathological changes.

Continuous monitoring of uterine activity has therefore gained increasing importance. Traditional external tocodynamometry measures mechanical changes associated with uterine contractions but often suffers from signal artefacts related to maternal movement, obesity, and sensor displacement. Advances in wearable uterine electromyography (electro hysterography) have improved contraction detection by recording the electrical activity generated by uterine smooth muscle before mechanical contractions become clinically apparent. When combined with AI algorithms, these physiological signals may predict preterm labour several hours or even days before clinical diagnosis[2].

## 3. Physiology of uterine contractions and fetal monitoring:

### 3.1. Physiology of uterine contractions:

The uterus is a highly specialized muscular organ composed primarily of smooth muscle fibres known as the myometrium, which plays a fundamental role in maintaining pregnancy and initiating childbirth. During most of pregnancy, the myometrium remains in a relatively quiescent state, allowing uninterrupted fetal growth. This uterine relaxation is maintained through the coordinated action of progesterone, nitric oxide, relaxing,

ISSN: 3107-9245, SJNS
Scienxt Journal of Nursing Studies

prostacyclin, and various intracellular signalling pathways that suppress myometrial excitability. As pregnancy approaches term, biochemical, hormonal, inflammatory, and mechanical changes progressively transform the uterus into a highly contractile organ capable of producing synchronized contractions necessary for labour.

Uterine contractions are generated by spontaneous electrical depolarization of myometrial smooth muscle cells. These electrical impulses propagate through specialized intercellular channels called gap junctions, composed primarily of connexin-43 proteins. During late pregnancy, the number of gap junctions increases significantly, enabling coordinated propagation of electrical activity throughout the uterus. This synchronization allows contractions to become stronger, longer, and more effective in facilitating cervical dilatation and fetal descent.

The initiation of labour is regulated by a complex interaction between maternal, fetal, placental, endocrine, and immune factors. Functional progesterone withdrawal increases uterine sensitivity to stimulatory hormones, particularly oxytocin and prostaglandins. Simultaneously, oestrogen enhances oxytocin receptor expression and promotes gap junction formation. Mechanical stretching of the uterus by the growing fetus further stimulates the production of inflammatory mediators and prostaglandins, increasing myometrial contractility.

Oxytocin, secreted by the posterior pituitary gland, binds to oxytocin receptors on myometrial cells, activating phospholipase C and increasing intracellular calcium concentrations. Elevated intracellular calcium activates myosin light-chain kinase, resulting in smooth muscle contraction. Prostaglandins, particularly prostaglandin $E_2$ and prostaglandin $F_{2}\alpha$, enhance uterine contractility while simultaneously promoting cervical ripening through collagen degradation and extracellular matrix remodelling[3].

Each uterine contraction follows a characteristic pattern consisting of four phases:

1. Initiation phase – electrical depolarization begins within pacemaker regions.
2. Propagation phase – electrical signals spread across the myometrium.
3. Peak contraction – maximum uterine pressure is achieved.
4. Relaxation phase – calcium is removed from the cytoplasm, allowing muscle relaxation.

Normal labour contractions gradually increase in frequency, intensity, and duration while decreasing the interval between successive contractions. In contrast, preterm labour involves premature activation of these physiological mechanisms before 37 weeks of gestation.

## 3.2. Pathophysiology of preterm labour:

Preterm labour is a multifactorial syndrome rather than a single disease entity. Several independent biological pathways may prematurely activate uterine contractions.

## 3.3. Intrauterine infection:

Ascending bacterial infections from the lower genital tract stimulate maternal immune responses characterized by increased production of inflammatory cytokines including interleukin-1, interleukin-6, interleukin-8, and tumour necrosis factor-alpha. These inflammatory mediators stimulate prostaglandin synthesis, promoting uterine contractions and cervical ripening.

## 3.4. Decidual haemorrhage:

Placental bleeding activates thrombin production, which directly stimulates myometrial contractions while increasing prostaglandin synthesis.

## 3.5. Uterine overdistension:

Multiple pregnancies, polyhydramnios, and fetal macrosomia excessively stretch uterine muscle fibres, increasing mechanical activation of contraction-associated proteins.

## 3.6. Maternal stress:

Psychological and physiological stress activates the hypothalamic-pituitary-adrenal axis, increasing cortisol and corticotropin-releasing hormone production, which may accelerate fetal maturation and initiate premature labour[4].

## 3.7. Cervical insufficiency:

Structural weakness of the cervix permits painless cervical dilatation before term, often leading to spontaneous preterm birth.

These diverse mechanisms highlight why continuous physiological monitoring rather than isolated clinical assessment is increasingly recommended for high-risk pregnancies.

### 3.8. Characteristics of uterine contractions:

*Table. 1: Clinical Parameters of Uterine Contractions and Their Significance*

| Parameter | Clinical Significance |
|---|---|
| Frequency | Number of contractions in 10 minutes |
| Duration | Time from onset to completion |
| Intensity | Strength of contraction |
| Resting tone | Baseline uterine pressure between contractions |
| Regularity | Pattern consistency |
| Propagation | Direction and synchronization |

Modern wearable monitoring devices can automatically measure these characteristics with high precision using uterine electromyography (EHG) rather than relying solely on mechanical pressure sensors[5].

### 3.9. Uterine electromyography (electro hysterography):

Electro hysterography (EHG) records the electrical activity generated by uterine smooth muscle before mechanical contractions become clinically apparent.

Unlike traditional tocodynamometry, EHG measures the bioelectrical signals responsible for initiating contractions. These signals typically range between 0.1 and 4 Hz, requiring highly sensitive electrodes and sophisticated signal processing techniques.

Advantages of EHG include:

- Earlier detection of uterine activation
- Improved accuracy in obese women
- Reduced motion artifacts
- Continuous ambulatory monitoring
- Better prediction of preterm labour
- Compatibility with AI-based pattern recognition

Machine learning algorithms can analyse EHG signal amplitude, propagation velocity, spectral characteristics, entropy, and synchronization patterns to distinguish true labour from false labour.

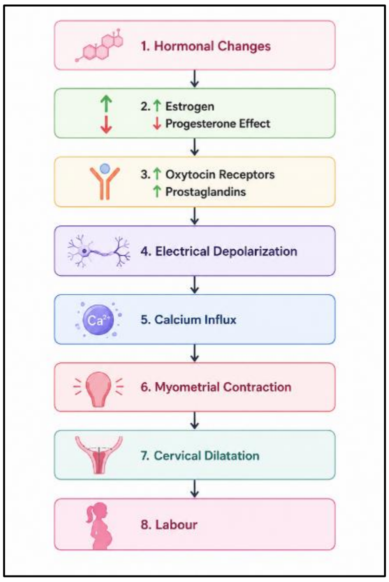


*Figure. 1. Physiological Mechanism of Uterine Contraction*

## 4. Fetal monitoring:

### 4.1. Importance of fetal monitoring:

Continuous fetal monitoring aims to assess fetal well-being throughout pregnancy by evaluating physiological indicators of oxygenation, neurological status, and cardiovascular function.

The fetus continuously adapts to changes in oxygen supply, placental perfusion, maternal physiology, and uterine contractions. Early identification of fetal compromise enables timely obstetric intervention before irreversible injury occurs[6].

Major objectives include:

- Detect fetal hypoxia
- Detect fetal distress
- Monitor fetal heart activity
- Evaluate fetal movement
- Assess uteroplacental circulation
- Predict adverse neonatal outcomes

Continuous monitoring is especially important among pregnancies complicated by:

- Hypertension
- Diabetes
- Preterm labour
- Intrauterine growth restriction
- Oligohydramnios
- Multiple pregnancy
- Placental insufficiency

## 4.2. Fetal heart rate:

Fetal heart rate (FHR) remains one of the most reliable indicators of fetal well-being.

Normal fetal heart rate ranges between:

## 4.3. 110–160 beats per minute:

Changes in fetal heart rate reflect autonomic nervous system function, oxygenation, neurological maturity, and cardiovascular adaptation.

Important FHR parameters include:

- Baseline heart rate
- Baseline variability
- Accelerations
- Decelerations
- Sinusoidal patterns

Artificial intelligence algorithms analyse thousands of heartbeat patterns simultaneously, detecting subtle abnormalities beyond human visual interpretation.

## 4.4. Fetal heart rate variability:

Heart rate variability represents beat-to-beat fluctuations controlled by sympathetic and parasympathetic nervous systems.

Normal variability indicates:

- Adequate oxygenation
- Healthy autonomic nervous system
- Intact neurological function

Reduced variability may indicate:

- Fetal hypoxia
- Acidosis
- Sleep cycles
- Drug exposure
- Neurological impairment

Deep learning algorithms demonstrate superior accuracy in identifying pathological variability compared with conventional cardiotocography interpretation.

## 5. Methods of fetal monitoring:

## 5.1. Intermittent auscultation:

Uses Doppler ultrasound or fetoscope.

Advantages

- Simple
- Low cost
- Portable

Limitations

- Intermittent assessment
- Misses transient abnormalities

### 5.2. Electronic fetal monitoring:

Uses cardiotocography (CTG).
Measures:

- Fetal heart rate
- Uterine contractions

Advantages

- Continuous monitoring
- Widely available

Limitations

- High false-positive rate
- Requires trained interpretation

### 5.3. Fetal electrocardiography:

Measures fetal cardiac electrical activity directly.
Advantages

- High signal accuracy
- Better rhythm analysis
- Continuous monitoring

Increasingly incorporated into wearable abdominal monitoring belts.

### 5.4. Fetal phonocardiography:

Records fetal heart sounds using sensitive microphones.
Advantages

- Non-invasive
- Comfortable
- Suitable for home monitoring

AI algorithms remove environmental noise while improving signal quality.

### 5.5. Wearable biosensor monitoring:

Modern wearable systems combine multiple sensors simultaneously.
These include:

- ECG
- EMG
- Accelerometer
- Temperature sensor
- Pulse oximeter
- Gyroscope
- Respiratory sensor
- Pressure sensor

The integration of multiple physiological signals substantially improves prediction accuracy[7].

## 6. Internet of things (IOT) in maternal healthcare:

### 6.1. Concept of IoT:

The Internet of Things refers to an interconnected ecosystem of intelligent physical devices capable of sensing, processing, transmitting, and exchanging information through wireless communication networks.
An IoT healthcare system generally consists of five components:

1. Sensors

2. Communication network
3. Edge processing
4. Cloud platform
5. Clinical application

Together these components enable continuous monitoring without requiring hospital admission.

## 7. Components of IOT-Based Maternal Monitoring:

### 7.1. Wearable biosensors:

Collect physiological information continuously.
Examples include:

- Uterine EMG
- Fetal ECG
- Maternal ECG
- Temperature
- Oxygen saturation
- Respiratory rate

### 7.2. Wireless communication:

Data transmission technologies include:

- Bluetooth Low Energy
- Wi-Fi
- ZigBee
- Lora WAN
- 4G
- 5G

Bluetooth remains most common for wearable pregnancy devices because of low energy consumption[8].

### 7.3. Smartphone gateway:

The smartphone acts as an intermediary between wearable sensors and cloud servers.
Functions include:

- Data collection
- Signal pre-processing
- Encryption
- Temporary storage
- GPS location
- Alert notification

### 7.4. Cloud computing:

Cloud platforms provide:

- Large-scale storage
- Remote accessibility
- AI model execution
- Data visualization
- Electronic health record integration

Cloud computing enables healthcare providers to monitor hundreds of pregnant women simultaneously[9].

### 7.5. Healthcare dashboard:

Clinical dashboards display:

- Real-time uterine contractions
- Fetal heart rate
- Maternal vital signs
- Risk prediction score
- Medication reminders
- Emergency alerts

These dashboards improve clinical decision-making while reducing documentation workload.

### 7.6. Advantages of IOT in Pregnancy Care:

The integration of IoT technologies into antenatal care offers numerous clinical and operational benefits:

- Continuous maternal surveillance
- Remote home monitoring
- Early detection of complications
- Reduced hospital admissions
- Improved access in rural settings
- Enhanced patient engagement
- Lower healthcare costs
- Faster emergency response
- Personalized antenatal care
- Seamless integration with telemedicine services

For obstetric nurses, IoT facilitates proactive care by enabling timely follow-up, remote patient education, and rapid response to abnormal physiological changes.

### 7.7. Wearable technologies for pregnancy monitoring:

Wearable technologies have transformed maternal healthcare by enabling continuous, non-invasive, and real-time monitoring of both maternal and fetal health. Unlike conventional antenatal assessments that occur only during scheduled hospital visits, wearable devices collect physiological data throughout daily activities, allowing early identification of complications such as preterm labour, fetal distress, and maternal cardiovascular abnormalities. These technologies improve clinical decision-making by providing healthcare professionals with continuous information rather than isolated observations[10].

Modern wearable pregnancy monitoring systems are designed as abdominal belts, adhesive sensor patches, smart garments, wristbands, and portable monitoring devices. These systems are lightweight, comfortable, and suitable for long-term use in home settings. Integrated biosensors measure uterine contractions, fetal heart rate, maternal heart rate, respiratory rate, body temperature, oxygen saturation, physical activity, and sleep patterns. The collected data are transmitted wirelessly through Bluetooth, Wi-Fi, or cellular networks to smartphones or cloud platforms for analysis.

The combination of wearable technology with IoT infrastructure enables remote monitoring by obstetricians and nurses. Automated alerts generated through mobile applications allow timely intervention when abnormal physiological patterns are detected. Such systems reduce unnecessary hospital visits, enhance patient convenience, and improve access to specialist care for women living in rural or underserved areas.

***Table. 2: Common Wearable Sensors Used in Maternal Monitoring***

| Sensor | Parameter Measured | Clinical Application |
|---|---|---|
| Uterine EMG (EHG) | Uterine electrical activity | Detection of uterine contractions |
| Fetal ECG | Fetal heart rate | Assessment of fetal well-being |
| Maternal ECG | Maternal heart rhythm | Detection of cardiovascular abnormalities |
| Pulse Oximeter | Oxygen saturation | Identification of maternal hypoxia |
| Temperature Sensor | Body temperature | Detection of infection or fever |
| Accelerometer | Physical activity and posture | Maternal mobility assessment |
| Respiratory Sensor | Respiratory rate | Monitoring respiratory function |

### 7.8. Artificial intelligence for early prediction of preterm labour:

Artificial intelligence (AI) has become an essential component of modern maternal healthcare by enabling predictive analysis of complex physiological data collected through wearable devices. Conventional monitoring often depends on manual interpretation of fetal heart rate patterns and uterine contractions, which may vary among healthcare providers. AI overcomes these limitations by identifying hidden relationships within large datasets and generating accurate risk predictions for preterm labour.

Machine learning algorithms analyse multiple maternal and fetal parameters simultaneously, including uterine contraction frequency, contraction duration, fetal heart rate variability, maternal heart rate, oxygen saturation, temperature, and previous obstetric history. By recognizing subtle physiological changes that precede clinical symptoms, AI systems can identify women at high risk of preterm labour several hours or days before conventional diagnosis.

ISSN: 3107-9245, SJNS
Scienxt Journal of Nursing Studies

Several machine learning techniques have demonstrated promising performance in maternal monitoring. Random Forest algorithms efficiently classify high-risk pregnancies using multiple clinical variables, while Support Vector Machines accurately distinguish true labour from false labour. Artificial Neural Networks and Deep Learning models process large volumes of physiological signals, improving prediction accuracy by recognizing complex temporal patterns. Long Short-Term Memory (LSTM) networks are particularly effective for analysing continuous time-series data such as uterine electromyography and fetal heart rate recordings.

AI-based clinical decision-support systems continuously compare incoming physiological data with trained predictive models. When abnormal patterns are detected, automated alerts are transmitted to healthcare professionals through cloud-based dashboards or mobile applications. These alerts facilitate early clinical assessment, administration of tocolytic therapy, antenatal corticosteroids, or referral to tertiary healthcare centres when necessary[11].

***Table. 3: Artificial Intelligence Techniques in Maternal Monitoring***

| AI Technique | Primary Application |
|---|---|
| Random Forest | Pregnancy risk classification |
| Support Vector Machine | Prediction of preterm labour |
| Artificial Neural Network | Pattern recognition |
| Deep Learning | Continuous physiological signal analysis |
| LSTM Network | Time-series prediction of uterine contractions |
| Ensemble Learning | Improved diagnostic accuracy |

### 7.9. System architecture of IOT-based wearable monitoring:

The IoT-based maternal monitoring system consists of interconnected hardware and software components that support continuous physiological surveillance.

The monitoring process begins with wearable biosensors attached to the mother's abdomen or wrist. These sensors continuously measure uterine contractions, fetal heart rate, maternal vital signs, and physical activity. Data are transmitted via Bluetooth or Wi-Fi to a smartphone, which serves as a gateway for secure communication with cloud servers.

Cloud computing platforms store and process the incoming data using AI algorithms. The analysed information is displayed on clinician dashboards, enabling obstetricians and nurses to monitor multiple patients remotely. If abnormal physiological patterns are detected, automated alerts are immediately sent to healthcare providers and the pregnant woman through mobile notifications.

### 7.10. Obstetric nursing management:

Obstetric nurses play a central role in the successful implementation of AI-assisted maternal monitoring systems. Their responsibilities extend beyond routine antenatal care to include interpretation of physiological data, patient education, remote monitoring, and coordination of multidisciplinary care.

Nurses educate pregnant women regarding the proper use of wearable devices, sensor placement, device maintenance, and interpretation of mobile application alerts. Continuous monitoring allows nurses to identify abnormal uterine activity or fetal heart rate changes before severe complications develop. When AI-generated alerts indicate increased risk, nurses perform clinical assessments, communicate findings to obstetricians, and initiate appropriate interventions according to institutional protocols.

Key nursing interventions include monitoring maternal vital signs, assessing contraction characteristics, evaluating fetal movement, promoting hydration, encouraging adequate rest, administering prescribed medications, providing emotional support, documenting clinical findings, and arranging referral to higher-level healthcare facilities when required. Nurses also ensure patient adherence to follow-up appointments and reinforce education regarding warning signs such as vaginal bleeding, leakage of amniotic fluid, decreased fetal movement, or regular painful contractions.

The integration of AI into obstetric nursing enhances clinical efficiency by reducing manual documentation, improving prioritization of high-risk patients, and facilitating evidence-based decision-making. However, clinical judgment remains essential, and AI should complement rather than replace professional nursing assessment[12].

### 7.11. Clinical applications, advantages, challenges, and future perspectives:

IoT-enabled wearable monitoring systems have demonstrated significant potential in improving maternal and neonatal healthcare. Continuous remote monitoring facilitates early detection of preterm labour, fetal distress, hypertensive disorders of pregnancy, gestational diabetes-related complications, and maternal infections. Home-based monitoring reduces unnecessary hospital visits while ensuring continuous surveillance of high-risk pregnancies.

The principal advantages include continuous real-time monitoring, early diagnosis, improved patient safety, personalized care, reduced healthcare costs, enhanced access for rural populations, and strengthened communication between patients and healthcare providers. AI-assisted analysis also minimizes observer variability and improves diagnostic accuracy.

Despite these advantages, several challenges remain. Sensor accuracy may be affected by maternal movement, obesity, poor electrode placement, and environmental interference. Data privacy, cybersecurity, interoperability between healthcare systems, regulatory approval, and algorithm transparency continue to present important concerns. Limited internet connectivity and digital literacy may also restrict implementation in resource-limited settings.

Future maternal healthcare is expected to integrate wearable sensors with fifth-generation (5G) communication networks, cloud computing, digital twins, explainable artificial intelligence, and precision medicine. These innovations will enable increasingly personalized pregnancy management through continuous learning from large clinical datasets. Further multicenter clinical trials are required to validate predictive models across diverse populations before widespread adoption into routine obstetric practice[13].

## 12. Conclusion:

Preterm labour remains a major contributor to maternal and neonatal morbidity and mortality worldwide, emphasizing the need for innovative strategies that support early detection and timely intervention. IoT-based wearable uterine contraction and fetal monitoring systems represent a significant advancement in digital maternal healthcare by enabling continuous, non-invasive, and remote surveillance throughout pregnancy. The integration of wearable biosensors with artificial intelligence allows real-time analysis of uterine activity, fetal heart rate, and maternal physiological parameters, facilitating accurate prediction of preterm labour and early recognition of fetal compromise.

Artificial intelligence enhances conventional monitoring by identifying subtle physiological changes that may not be recognized through manual interpretation alone. Automated clinical decision-support systems assist healthcare professionals in prioritizing high-risk pregnancies and initiating evidence-based interventions at an earlier stage. Obstetric nurses play a pivotal role in implementing these technologies through patient education, continuous monitoring, interpretation of AI-generated alerts, and coordination of multidisciplinary care.

Although challenges related to data security, interoperability, clinical validation, and accessibility remain, continued technological innovation and evidence-based implementation are expected to transform maternal healthcare from reactive management to predictive and preventive care. The integration of IoT and AI into obstetric nursing practice has the potential to improve pregnancy outcomes, reduce healthcare costs, and contribute significantly toward achieving global maternal and neonatal health goals.

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