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# Wearable Technology in Women's Health: A Review of Applications for Fertility Tracking and Pregnancy Monitoring

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## Abstract

The integration of wearable technology into women's health represents a significant advancement in personalized healthcare, particularly in the domains of fertility tracking and pregnancy monitoring. This review highlights the growing need to consolidate current evidence on the efficacy, applications, and limitations of these technologies to inform future research and clinical practice. As wearable devices become increasingly prevalent, a comprehensive evaluation of their role in enhancing reproductive health outcomes is essential. This review covers the use of wearables for monitoring key physiological parameters such as basal body temperature, heart rate variability, and respiratory rate to predict ovulation and fertile windows. It also examines devices designed for continuous pregnancy monitoring, including those tracking maternal heart rate, fetal movements, and sleep patterns. The accuracy and validation of various wearable technologies are discussed, alongside user acceptability and engagement. The review further addresses the integration of artificial intelligence (AI) and internet of things (IoT) technologies in enhancing data analysis and predictive capabilities. Clinical evidence supporting the use of these devices is summarized, and challenges related to data privacy, ethical considerations, and regulatory gaps are explored. Looking ahead, future efforts should focus on refining sensor technologies and algorithms to improve accuracy across diverse populations and cycle variations. There is also a need for large-scale, longitudinal studies to validate health outcomes and ensure equitable access to these innovations. Ultimately, wearable technology holds promise for transforming reproductive healthcare into a more proactive, individualized, and accessible discipline.

**Keywords:** Digital health, Fertility tracking, Ovulation detection, Physiological monitoring, Pregnancy monitoring, Wearable technology, Women's health

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## Introduction

The advent of wearable technology has significantly transformed various facets of healthcare, including women's reproductive health, fertility tracking, and pregnancy monitoring [1-6]. Analyzing the current literature reveals a burgeoning interest in leveraging wearable devices to enhance maternal health outcomes, facilitate personalized care, and address specific physiological monitoring needs during pregnancy [7-9]. One of the primary applications of wearable technology in women's health pertains to fertility tracking. Wearable devices have been increasingly utilized to monitor physiological parameters that are indicative of ovulation and fertility status [10-15]. Maugeri et al. [16] conducted a scoping review that systematically mapped the literature on wearable sensors in the context of fetal and pregnancy outcomes, emphasizing their potential to support personalized antenatal care. Similarly, Liu et al. [17] highlighted the integration of physiological data processing and AI in pregnancy monitoring, underscoring the role of wearable sensors in capturing vital signs relevant to fertility and pregnancy health. These devices enable continuous, non-invasive tracking of parameters such as body temperature, heart rate, and hormonal fluctuations, which are critical for identifying fertile windows and optimizing conception timing [18-21].

Furthermore, the literature indicates that wearable technology can provide valuable insights into hormonal and physiological changes associated with ovulation, especially in women with conditions like polycystic ovary syndrome [22, 23]. Vause et al. [24] reviewed ovulation induction options in polycystic ovary syndrome, although their focus was primarily on pharmacologic and non-pharmacologic interventions rather than wearable devices. Nonetheless, the potential for wearable technology to complement such interventions by offering real-time ovulation prediction remains promising, as continuous monitoring could improve the accuracy of fertility assessments.

In the realm of pregnancy monitoring, wearable devices have been

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explored for their capacity to track maternal physiological parameters and environmental exposures [25-29]. Radin et al. [30] emphasized that digital tracking tools could better characterize a woman's individual health trajectory during pregnancy, potentially identifying early deviations that signal adverse outcomes. This personalized approach is further supported by Li et al. [31], who conducted qualitative interviews with pregnant women and clinicians, revealing perceptions that mHealth and wearable technologies could enhance engagement and improve monitoring of maternal health. These perceptions suggest that wearable devices could serve as accessible tools for continuous monitoring, thereby facilitating early intervention and tailored care.

Specific physiological parameters monitored by wearables include heart rate variability, sleep patterns, blood pressure, and environmental exposures (Table 1) [32-35]. Jafleh et al. [36] reviewed the role of wearable devices across various medical fields, including endocrinology and obstetrics, noting their utility in fertility tracking and pregnancy management. The potential of heart rate variability as a stress biomarker during pregnancy has been highlighted by Byfield et al. [37], who conducted a scoping review on heart rate variability measurement among pregnant and postpartum women. Their findings suggest that heart rate variability monitoring via wearables could serve as an indicator of stress and mental health, which are critical factors influencing pregnancy outcomes. Sleep monitoring is another area where wearable technology shows significant promise. Balkan et al. [38] reviewed portable sleep monitoring devices in pregnancy, emphasizing their potential to estimate perinatal outcomes and identify sleep-disordered breathing, which can adversely affect maternal and neonatal health. Although more research is needed to standardize these tools, their application could provide valuable data on sleep quality and disturbances during pregnancy, contributing to comprehensive maternal health assessments.

Despite the promising applications, challenges remain in the widespread adoption of wearable technology for women's health. Muzny et al. [39] identified limited research on perceptions among pregnant women and healthcare providers regarding wearable sensors, indicating that user acceptance and integration into clinical practice are areas requiring further exploration. Additionally, security concerns related to data privacy and cybersecurity risks associated with IoT-based wearables have been discussed by Sam et al. [40], emphasizing the need for robust safeguards to protect sensitive health data. The commercial landscape of wearable health devices is expanding, with various products tailored for different populations, including pregnant women and seniors. Tedesco et al. [41] reviewed activity trackers for senior citizens, highlighting the acceptability and limitations of consumer-grade devices, which could inform the development of pregnancy-specific wearables. Consumer perceptions and usability are critical factors influencing the effectiveness of these devices, as explored by Chong et al. [42], who analyzed user reviews and found that ease of use and accuracy significantly impact user engagement.

Overall, the literature underscores the significant potential of wearable technology to revolutionize women's reproductive health by enabling continuous, personalized monitoring of fertility and pregnancy parameters. These devices can facilitate early detection of complications, improve patient engagement, and support tailored interventions. However, challenges related to user acceptance, data security, and standardization need to be addressed to fully realize their benefits. As research progresses, integrating wearable sensors with advanced data analytics and AI holds promise for transforming maternal healthcare into a more proactive and individualized discipline, ultimately improving outcomes for mothers and their babies.

## Fertility Tracking

Wearable devices have revolutionized fertility tracking by enabling women to monitor physiological changes associated with their menstrual cycles (Table 2). Recent studies have shown that these devices can effectively track various stages of the menstrual cycle, including ovulation and menstruation, by assessing changes in heart rate, temperature, and respiratory rate [45]. The accuracy of these wearables in predicting fertility windows has been validated, making them a promising tool for women seeking to conceive. Moreover, the user experience plays a crucial role in the adoption of fertility tracking technologies. Research indicates that women are more likely to engage with wearable devices if they perceive them as beneficial and if their data is monitored by healthcare professionals [31]. This highlights the importance of designing user-friendly interfaces and ensuring data privacy to foster trust and compliance among users.

### Types of wearable devices

- Wristbands and bracelets: Devices like the Ava bracelet monitor wrist skin temperature, heart rate, and respiratory rate to detect phase-based shifts in the menstrual cycle. These wearables have demonstrated the ability to predict the fertile window with high accuracy, utilizing machine learning algorithms to enhance detection capabilities [54, 56].

- Rings: The Oura ring uses physiological data from the finger to estimate ovulation dates, outperforming traditional calendar methods in accuracy. It remains effective across various cycle lengths and participant ages, highlighting its robustness in diverse conditions [46].

**Table 1:** Key physiological parameters for fertility and pregnancy monitoring.

| Parameter | Role in fertility tracking | Role in pregnancy monitoring | Monitoring method(s) |
|---|---|---|---|
| Temperature | Gold standard for retrospective ovulation confirmation (biphasic pattern). Wrist skin temperature is more resilient to lifestyle confounders | Less commonly used, but can indicate maternal fever or infection | Wristbands, rings, in-ear sensors, patches |
| Heart rate | Increases around ovulation and remains elevated in the luteal phase | Resting heart rate increases significantly (e.g., +17%) during pregnancy and returns to baseline postpartum | Wristbands, rings, chest straps |
| Heart rate variability | Fluctuates with menstrual cycle phases | A potential biomarker for maternal stress and mental health; may indicate pregnancy complications | Wristbands, rings, chest straps |
| Respiratory rate | Preliminary evidence of changes across the menstrual cycle; requires more validation | Can be used to screen for sleep-disordered breathing, a risk factor in pregnancy | Wristbands, chest straps |
| Physical activity | Can influence cycle regularity and overall health | Declines significantly from 2$^{nd}$ to 3$^{rd}$ trimester and into postpartum. Important for managing weight and health | Wristbands (accelerometry) |
| Sleep patterns | Sleep quality can impact hormonal regulation | Total sleep time decreases, and nighttime awakenings increase as pregnancy progresses | Wristbands, rings (actigraphy) |

**Table 2:** Few studies reported in literature that investigated wearable devices for fertility tracking.

| Accuracy of fertility tracking | Health outcome impact | Accessibility and user acceptability | Integration of AI and IoT | Future innovation potential | Ref. |
|---|---|---|---|---|---|
| High accuracy (99.2%) in labor onset detection | Improved maternal care in rural areas | Designed for remote, underserved populations | IoT-enabled real-time alerts | Scalable, cost-effective remote monitoring | [43] |
| Moderate accuracy for heart rate and sleep; low for pregnancy tracking | Limited evidence on health outcomes | High acceptability for fertility, low for pregnancy | Basic sensor integration | Need for further validation and utility studies | [44] |
| High accuracy in detecting fertility phases via physiological signals | Potential for fertility management | Limited consumer perspective data | Wearables measuring multiple physiological parameters | Calls for ethical data privacy research | [45] |
| Physiology method 2.7x more accurate than calendar method | Not directly assessed | Stable performance across ages and cycle types | Physiology-based ovulation estimation | Enhanced reliability for irregular cycles | [46] |
| Mean absolute error ~1.2 to 1.6 days for ovulation prediction using wrist temperature | Supports menstrual cycle tracking | Algorithms applicable to typical and atypical cycles | Algorithmic temperature data processing | Integration with other physiological measures | [47] |
| Cosinor model effectively characterizes menstrual skin temperature rhythms | Enables menstrual health markers | Data from 120 participants in real-world setting | Advanced modeling of temperature data | Potential for menstrual chronotherapy applications | [48] |
| Fertile window prediction accuracy ~87% using basal body temperature and heart rate | Fertility window and menses prediction | Lower accuracy in irregular menstruators | Machine learning algorithms applied | Algorithm refinement for irregular cycles | [49] |
| Retrospective algorithm identifies ~75% fertile days accurately | Not directly linked to outcomes | Large real-world data validation | Wrist-worn sensor algorithms | Prospective fertile window detection improvements | [50] |
| Wrist skin temperature more sensitive than basal body temperature for ovulation | Enhanced ovulation detection sensitivity | Continuous, non-invasive monitoring | Continuous temperature measurement | Potential to replace traditional basal body temperature methods | [51] |
| Menstrual prediction accuracy within ±3 days at 92.55% | Not directly assessed | User-friendly smart ring device | Temperature trend analysis | Foundation for future menstrual prediction tools | [52] |
| Smartphone Inertial Measurement Unit signals predict menstrual onset with 0.56-day error | Convenience in menstrual tracking | Robust across demographics and devices | Attention-based prediction model | Meta-learning for new user generalization | [53] |
| Wrist skin temperature detects biphasic cycle shifts in 82% of cycles | Robust to environmental confounders | High user compliance challenges noted | Multiparameter wearable data integration | Combining wearables with luteinizing hormone tests for fertility | [54] |
| 90% accuracy in ovulation window prediction vs ultrasound | Comparable to physician assessment | User-friendly, accessible device | IoT-based basal body temperature sensor | Digital ovulation monitoring platform | [55] |

- In-ear thermometers: These devices measure ear canal temperature to detect ovulation, offering significant improvements in detection accuracy over traditional methods. The use of high-frequency temperature data and statistical learning algorithms enhances their predictive power [57].

## Physiological parameters monitored

- Temperature: Basal body temperature and wrist skin temperature are key indicators of ovulation. Wearables can detect subtle temperature shifts that occur during the menstrual cycle, providing a reliable method for fertility tracking [54, 57].

- Heart rate and variability: Changes in heart rate and heart rate variability are associated with different phases of the menstrual cycle. Wearables can monitor these parameters to identify the fertile window and other cycle stages [50, 56].

- Respiratory rate: Although less commonly used, respiratory rate changes can also indicate menstrual cycle phases. More research is needed to validate its effectiveness as a fertility tracking parameter [45].

## Accuracy and validation

Wearable devices generally show high accuracy in detecting fertility and differentiating between menstrual cycle stages. For instance, wearable devices like the Ava bracelet and O'Tracker have demonstrated high accuracy in detecting ovulation by monitoring changes in basal body temperature and heart rate. The Ava bracelet, for instance, achieved a 90% accuracy rate in predicting the fertile window by analyzing multiple physiological parameters simultaneously. Similarly, the O'Tracker device showed a 90% accuracy rate when compared to ultrasound predictions, highlighting its reliability in ovulation detection. The integration of machine learning algorithms has further enhanced the accuracy of these devices. For example, the Ava bracelet uses a machine learning algorithm to detect the fertile window with a 90% accuracy rate, showcasing the potential of AI in improving fertility tracking [56].

Similarly, the Oura ring's physiology method has a mean absolute error of 1.26 days in estimating ovulation dates, significantly outperforming the calendar method. The Oura ring's physiology method was found to be 2.7 times more accurate than the calendar method, particularly in cycles with irregular lengths [46]. Wearable devices have been compared with traditional methods such as urinary ovulation tests and calendar methods. The RingConn smart ring, for instance, achieved a prediction accuracy of 92.55% within ±3 days, demonstrating its effectiveness compared to self-reported methods [52]. Studies have validated the accuracy of wearable devices in both clinical settings and real-world applications. For example, a study involving wrist-worn devices confirmed their ability to accurately detect the periovulatory period, with a mean error of 0.31 days in identifying ovulation [50]. This validation is crucial for ensuring the reliability of these devices in everyday use.

While wearable technology offers significant advancements in fertility tracking, challenges such as data privacy, cost, and user acceptance need to be addressed to fully realize its potential. Additionally, further research is necessary to validate the effectiveness of various physiological parameters and to explore the integration of these technologies into broader reproductive health care strategies.

# Pregnancy Monitoring

The application of wearable technology in pregnancy monitoring is gaining traction, with devices capable of tracking maternal and fetal health metrics. Wearable electrocardiogram devices, for instance, allow pregnant women to monitor their heart health and that of their fetuses remotely [58-60]. A study found that a significant majority of women expressed willingness to use such devices for continuous monitoring throughout their pregnancy [61]. This acceptance underscores the potential of wearables to enhance prenatal care by facilitating timely interventions and reducing the need for frequent hospital visits. Additionally, wearable sensors can monitor vital signs such as heart rate variability and resting heart rate, providing insights into cardiovascular health during pregnancy. Research has demonstrated significant changes in these metrics throughout pregnancy, indicating the potential for wearables to identify health issues early [62]. Furthermore, the integration of AI in data processing can enhance the accuracy of health assessments, enabling personalized care strategies [17].

A study Wakefield by [61] involved a sample of 507 women, aged 18 to 45, from 45 states in the United States. These participants were expecting to become pregnant within the next five years. A significant majority, 461 out of 507 women (91%), expressed acceptance of wearable electrocardiogram technology for monitoring maternal and fetal health throughout pregnancy, especially for increased frequency of monitoring outside a hospital setting. Most participants, 395 out of 507 women (78%), showed a willingness to wear such devices either day and night or at least during sleep. A notable portion of the women, 213 out of 507 (42%), indicated they would be willing to spend up to $200 on such a device. The study concluded that there is a high degree of readiness among prospective pregnant women for telemedicine solutions that offer continuous health monitoring of the mother-fetus dyad, despite the study being conducted prior to the COVID-19 pandemic. These results highlight a strong interest and acceptance among prospective pregnant women for remote fetal electrocardiogram monitoring technologies, indicating a promising future for wearable health devices in maternal-fetal medicine.

A study by Bruce et al. [63], utilizing multimodal wearable device data, specifically the Oura Ring, across 120 individuals, yielded several significant findings regarding continuous physiological monitoring during pregnancy. The analysis of wearable device data demonstrated clear physiological trajectories throughout the entire pregnancy cycle, from pre-conception (cycling) through conception and into postpartum recovery. The study identified associated deviations in individuals whose pregnancies did not progress past the first trimester. This finding suggests that continuous monitoring provides new information that could aid in early decision-making during pregnancy. The research did not find significant physiological deviations between full-term pregnancies of individuals younger than 35 and those with 'advanced maternal age'. This indicates that continuous, individualized data analysis can enhance risk assessment, moving beyond standard population-based comparisons. The findings collectively demonstrate the feasibility of implementing low-cost, high-resolution physiological monitoring throughout all stages of pregnancy in real-world settings. This technology opens avenues for future studies into specific demographics, risks, and other aspects of pregnancy. In summary, the paper highlights the potential of wearable technology to provide continuous, high-resolution physiological data throughout pregnancy, offering insights into individual trajectories, aiding in early detection of complications, and refining risk assessments beyond traditional methods.

While wearable technology offers promising advancements in pregnancy monitoring, it is essential to address the challenges of data privacy, device accuracy, and user compliance to maximize its potential benefits. Additionally, efforts to increase awareness and accessibility, particularly in low-resource settings, are crucial for broader adoption. The integration of AI and IoT in wearable devices continues to evolve, offering new opportunities for improving maternal and fetal health outcomes.

## Clinical Studies

Wearable technology has emerged as a significant tool in fertility tracking and pregnancy monitoring, offering innovative solutions for reproductive health management. These devices, which include wristbands, rings, and patch-like sensors, are designed to track physiological changes such as temperature, heart rate, and respiratory rate, providing valuable insights into menstrual cycles and pregnancy progression. The integration of wearable technology into reproductive health care is promising, yet it also presents challenges that need to be addressed for broader adoption and effectiveness.

A study by Godbole et al. [55] evaluated the accuracy of O'Tracker, an IoT-based device, in predicting the ovulation window compared to transvaginal ultrasound reports in women trying to conceive. The O'Tracker device demonstrated a commendable accuracy rate of 90% in predicting the ovulation window. This was determined by aligning its predictions with physicians predicted ovulation windows derived from ultrasound reports. Out of 30 cycles scrutinized, O'Tracker's predictions for the ovulation window aligned with physician-predicted windows from ultrasound reports in 27 cycles. When considering the 27 accurately predicted ovulatory cycles, the concordance between O'Tracker's predicted ovulation window and those derived from ultrasound reports (considered the ground truth) was observed in 25 cycles. Compared to the physician-predicted ovulation window from ultrasound reports, O'Tracker exhibited concordance in 23 out of 27 cycles. The study concluded that O'Tracker achieves a 90% accuracy in predicting ovulation compared to physician assessment, showing a match rate exceeding 90% with fertile windows ascertained through ultrasound monitoring. In summary, O'Tracker showed high accuracy and concordance with traditional ultrasound monitoring and physician assessments, positioning it as a precise and user-friendly digital platform for ovulation monitoring.

A study by Shilaih et al. [54] investigated the correlation between wrist skin temperature and different phases of the menstrual cycle, offering insights into its potential as a fertility awareness method. A shift in skin temperature was observed in 82% of the menstrual cycles analyzed. The majority of these detected temperature shifts (86%) occurred on or after the day of ovulation. The choice of temperature threshold minimally affected these numbers; for instance, a 0.15 ˚C threshold yielded 88% and 84% for shift detection and timing, respectively. The lowest temperature in a given cycle, often occurring prior to ovulation, was frequently observed outside the fertile window. Specifically, the nadir was detected within the fertile window (ovulation-5 to ovulation) in only 41% of the 357 cycles. While 12% of cycles showed a wrist skin temperature nadir after ovulation, the remaining 47% had the lowest wrist skin temperature reading before the fertile window. Overall, 88% of the biphasic cycles in the study exhibited a wrist skin temperature nadir prior to ovulation. No participants had exclusively monophasic temperature patterns or temperature shifts occurring solely before ovulation. Consistent with traditional basal body temperature tracking, average wrist skin temperature during the menstrual phase (mean 35.32 ˚C, standard deviation (SD) 0.71) was significantly lower than during the early-luteal (mean 36.04 ˚C, SD 0.69) and late-luteal phases (mean 35.70 ˚C, SD 0.63). Women also exhibited significantly lower wrist skin temperature (mean 35.23 ˚C, SD 0.67) in their fertile phase compared to their menstrual phase wrist skin temperature. The study found that wrist skin temperature measurements were robust to several environmental factors that typically skew traditional basal body temperature readings. The main effects of phase shift remained significant even when controlling for covariates. Spotting, age, coffee consumption, and exercise within 3 h before sleep did not significantly affect wrist skin temperature. Although a higher body mass index was associated with lower wrist skin temperature, the direction and magnitude of menstrual phase shifts on wrist skin temperature remained unchanged. Having sex and eating a large meal within 3 h before bed were associated with increases in nightly wrist skin temperature, but the effect of the menstrual phase on wrist skin temperature persisted. The biphasic shifts in wrist skin temperature across the menstrual cycle were detectable regardless of individual behavior or activities prior to sleep, marking a significant difference from traditional basal body temperature readings. In summary, the study demonstrates that wrist skin temperature, measured by wearable devices, exhibits a biphasic pattern similar to basal body temperature during the menstrual cycle. While it effectively confirms ovulation retrospectively, it does not reliably predict it prospectively. A key advantage of wrist skin temperature is its resilience to lifestyle factors that often confound traditional basal body temperature measurements.

A study by Hurst et al. [64] evaluated the accuracy of a novel skin-worn sensor and its associated algorithm for confirming and predicting ovulation in women with ovulatory dysfunction, comparing it against a vaginal sensor and existing basal body temperature algorithms. The skin-worn sensor and its algorithm demonstrated 66% accuracy for determining the day of ovulation (within ±1 day) or the absence of ovulation. It was 90% accurate for identifying the fertile window (ovulation day ±3 days) when compared to the vaginal sensor and its algorithm, which served as the gold standard. The skin-worn sensor showed higher sensitivity (91%) than the traditional 'three over six' rule (79%) for the ±1-day threshold, indicating its better ability to correctly identify positive ovulations. For the fertile window (±3 days), skin-worn sensor achieved an accuracy of 90% and an F score of 0.93 for the combined study population. The 'Training set' (used for algorithm development) showed higher skin-worn sensor accuracy for both ±1 day and ±3 days analyses compared to the 'Additional Set,' suggesting some 'over-tuning' of the algorithm to the training data (Figure 1). Despite this, skin-worn sensor generally outperformed traditional

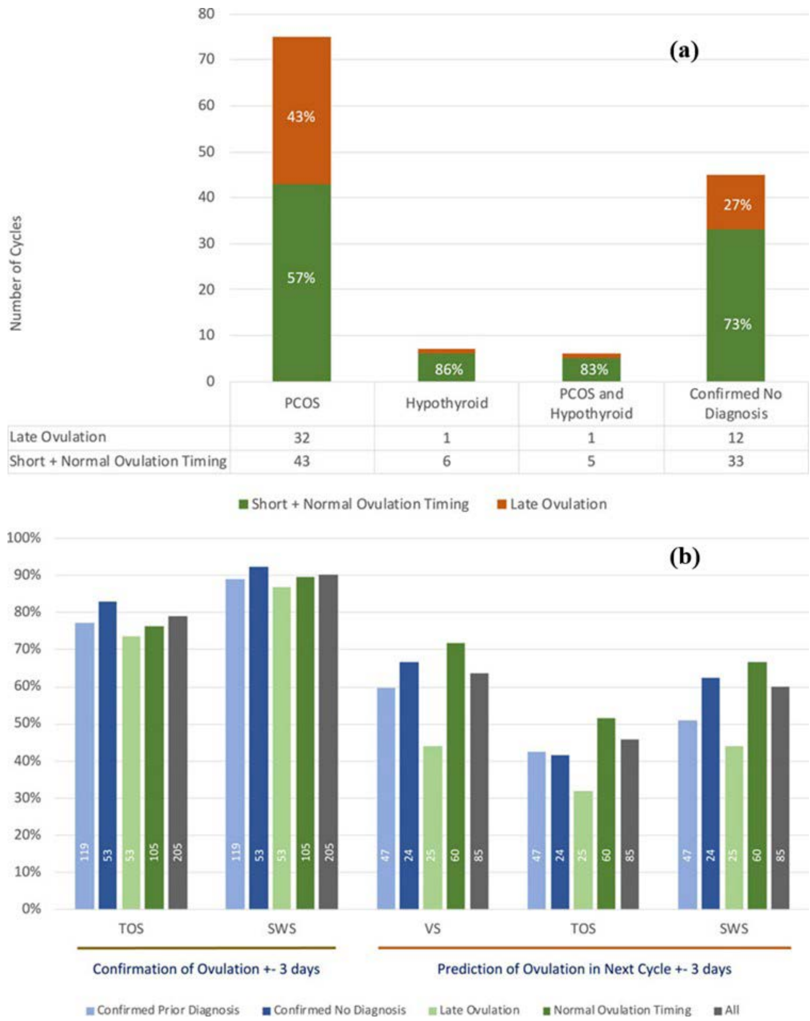


**Figure 1: (a)** Illustrates the correlation between the timing of ovulation and a confirmed diagnosis within the study group, with the number of cycles for each category presented in a table. **(b)** Displays the percentage accuracy for both confirming and predicting ovulation within a ±3-day window in subsequent cycles, utilizing the median day of ovulation prediction method. The figure includes annotations indicating the number of cycles used in each analysis [64].

'three over six' rule. A significant difference in median cycle lengths between the training and additional sets ($p = 0.0291$) might explain the poorer performance of the algorithm in the Additional Set group. The study found no significant difference in ovulation confirmation performance for skin-worn sensor between the arm and wrist sites, suggesting that skin-worn sensor can function equally well on either site. Interestingly, the wrist site outperformed the arm site in terms of accuracy and F score, particularly for the ±3 days threshold (94% accuracy, 0.96 F score for wrist vs 89% accuracy, 0.92 F score for arm). This might be due to better contact or higher protocol compliance by participants wearing the sensor on the wrist. The skin-worn sensor showed similar accuracy (66%) to three over six (65%) for the ±1-day threshold in the 'confirmed no diagnosis' group, and slightly better accuracy (66%) than traditional 'three over six' rule (65%) in the 'confirmed prior diagnosis' group. For the ±3 days threshold, skin-worn sensor consistently showed noticeably higher accuracy across all diagnosis and ovulation timing groups compared to three over six. Skin-worn sensor appears to be effective in populations with ovulatory dysfunction, whether previously diagnosed or not, indicating its utility despite the challenges of erratic temperature curves in such cases. Skin-worn sensor demonstrated a surprisingly similar prediction accuracy to vaginal sensor for subsequent cycles (skin-worn sensor: 60.0%, vaginal sensor: 63.5% for ±3 days threshold). Removing 'late ovulation' results improved prediction accuracy for both methods (skin-worn sensor: 66.7%, vaginal sensor: 71.7%), suggesting that identifying such cycles could aid in improving algorithms for women with ovulatory dysfunction. Vaginal sensor and skin-worn sensor methods produced similar accuracy and F scores for prediction, while traditional 'three over six' rule's accuracy was lower due to a higher number of false negatives. In summary, the skin-worn sensor offers a useful and relatively accurate method for confirming ovulation and the fertile window, particularly in populations with ovulatory dysfunction, and shows promise for predicting ovulation in subsequent cycles.

A study by Saarikko et al. [65], which utilized an IoT-based system and smart wristbands, revealed significant changes in health parameters among nulliparous women during pregnancy and the postpartum period. The findings highlight the feasibility of continuous monitoring and provide insights into physical activity, sleep patterns, and heart rate variations. Valid physical activity data was available for a median of 144 days (75% of possible monitoring days) during pregnancy and 15 days (54% of possible monitoring days) during the postpartum period. Physical activity, measured by step counts, significantly decreased from the second trimester to the third trimester by an average of 1793 steps per day ($p < 0.001$). This decline continued into the postpartum period, with a further decrease of 1339 steps per day ($p = 0.004$). The average daily step count ranged between 6000 and 7000 from 13 to 31 gestational weeks, dropping to 5000 by 36 gestational weeks and further to approximately 4000 steps/day thereafter. The most notable decrease occurred at 32 gestational weeks ($p < 0.05$). The intensity of physical activity also decreased from the second trimester to the postpartum period. Only a minority of participants met the recommended moderate-to-vigorous physical activity levels for pregnant women, with 47% in the second trimester, 24% in the third trimester, and 25% in the postpartum period meeting the recommendation for at least one week. Valid sleep data was available for a median of 137 days (72% of possible monitoring days) during pregnancy and 16 days (57% of possible monitoring days) during the postpartum period. Sleep minutes decreased, and nightly awake minutes increased from the second trimester to the postpartum period. Participants slept a mean of 8 h during the second trimester, decreasing by 20 min in the third trimester ($p = 0.06$). Total night sleep time shortened by an additional 1 h after delivery ($p < 0.001$). Average daily sleep minutes were between 450 and 500 from 13 to 38 gestational weeks, decreasing to 435 min after gestational week 38 ($p < 0.05$). The mean resting heart rate progressively increased by 17% from 60 bpm at 13 gestational weeks to 70 bpm at 32 gestational weeks, maintaining this level until delivery. The resting heart rate returned to early pregnancy levels by 4 weeks postpartum. In summary, the study successfully demonstrated the feasibility of using IoT-based continuous monitoring for health parameters in pregnant and postpartum women. It revealed a consistent decrease in physical activity and sleep duration as pregnancy progressed and into the postpartum period, alongside a temporary increase in resting heart rate during pregnancy.

A study by Luo et al. [57] presents significant improvements in ovulation detection and prediction using a novel wearable device and statistical learning algorithm. The algorithms developed for the wearable device were compared against traditional methods. This comparison focused on the match rate with self-reported ovulation days, which were validated using an ovulation test kit. The proposed methods demonstrated substantial improvements in detection accuracy. Specifically, they achieved a sensitivity of 92.31%. The study also reported a significant increase in prediction power, ranging from 23.07% to 31.55% higher than traditional methods. These findings were derived from an empirical study involving a group of 34 users. In summary, the research successfully demonstrated the feasibility of reliable ovulation detection and prediction through a non-invasive wearable device that collects high-frequency temperature data. The developed algorithms significantly outperformed traditional methods in both accuracy and prediction capabilities, offering a user-friendly and reliable platform for fertility tracking.

A study by Zhu et al. [51] reported key findings on wrist skin temperature vs basal body temperature for ovulation detection. Wrist skin temperature demonstrated higher sensitivity (0.62 vs 0.23; $p < 0.001$) and a greater true-positive rate (54.9% vs 20.2%) for detecting ovulation compared to basal body temperature. This indicates that wrist skin temperature is more effective at identifying actual ovulations. However, wrist skin temperature also had a higher false-positive rate (8.8% vs 3.6%), leading to lower specificity (0.26 vs 0.70; $p = 0.002$) than basal body temperature. This means basal body temperature was better at correctly identifying non-ovulatory cycles. When a temperature shift was detected, the probability of ovulation was similar for both methods: 86.2% for wrist skin temperature and 84.8% for basal body temperature. Both temperatures had low negative predictive values (8.8% for wrist skin temperature and 10.9% for basal body temperature), meaning they were not reliable for ruling out ovulation if no temperature shift was observed. For ovulatory cycles, a significantly higher percentage of cycles showed at least one temperature shift on wrist skin temperature curves (62.4%) compared to basal body temperature curves (22.9%; $p < 0.001$). Despite detecting fewer shifts, the temperature shift occurred almost 2 days earlier on basal body temperature curves than on wrist skin temperature curves ($p < 0.001$). For anovulatory cycles, wrist skin temperature also showed a significantly higher percentage of cycles with a temperature shift (74% vs 30%; $p = 0.004$). A significant positive correlation between wrist skin temperature and basal body temperature was only observed in the follicular phase (rmcorr correlation coefficient = 0.294; $p = 0.001$). Both temperatures increased during the postovulatory phase, but wrist skin temperature showed a greater increase (range of increase: 0.50 °C vs 0.20 °C). The estimated daily difference between the two temperatures was greatest on day 2 after

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ovulation (0.64 ˚C). During the menstrual phase, wrist skin temperature exhibited a more significant and rapid decrease (from 36.13 ˚C to 35.80 ˚C) compared to basal body temperature (from 36.31 ˚C to 36.27 ˚C). Minimal changes and small variations in the estimated daily difference between the two temperatures were observed during the preovulatory phase, indicating agreement. Throughout the menstrual cycle, wrist skin temperature was generally lower than basal body temperature, and the mean between-phase temperature change was 11% higher for wrist skin temperature than for basal body temperature. In summary, while wrist skin temperature is more sensitive for detecting ovulation and shows more pronounced thermal changes across the menstrual cycle phases, basal body temperature exhibits higher specificity. Neither method alone provides a sufficiently high negative predictive value to reliably avoid unplanned pregnancy, highlighting the need for further validation studies for wearable devices in fertility tracking.

A study by Zhao et al. [66] proposed wearable system demonstrated reliable performance in classifying fetal movement time series signals (Figure 2). It achieved a specificity of 0.99 and a sensitivity of 0.77 for this classification task. This system is anticipated to offer a valuable alternative for optimizing the utilization of medical professionals and hospital resources. It also holds potential for applications in e-Health home care. Furthermore, the fetal movement acceleration signals collected from pregnant volunteers will contribute to establishing an initial database for future medical analysis of sensor-recorded fetal behaviors.

A study by Du et al. [67] evaluated a wearable device designed for long-term monitoring of fetal movement, focusing on its ability to assess relative position, force, and duration. The results were derived from both phantom simulation tests and clinical tests involving pregnant women. The device demonstrated high accuracy in recognizing 12 different fetal movement positions, achieving an accuracy greater than 90.3%. The measurement of relative force showed a strong correlation, with an R-squared value greater than 0.98. The device exhibited a low error percentage, less than 10%, when evaluating the duration of fetal movements. The number of fetal movements detected by the device during clinical tests was consistent with the pregnant women's own perceptions. A questionnaire administered to the pregnant women indicated a high level of acceptance for the device. In summary, the phantom tests confirmed the device's high accuracy for position, strong correlation for force, and low error for duration, while clinical tests showed its effectiveness in matching self-perceived movements and high user acceptance, supporting its feasibility for home monitoring.

Overall, wearable technology offers promising advancements in fertility tracking and pregnancy monitoring, providing valuable insights into reproductive health. However, challenges related to data privacy, cost, and technological limitations must be addressed to fully realize their potential. As research continues to evolve, these devices could significantly enhance personal health management and clinical care in reproductive health.

## Challenges and Limitations

Despite the promising applications of wearable technology in women's health, several challenges remain. Data privacy and security concerns are paramount, as users may be hesitant to share sensitive health information. Additionally, the clinical integration of wearable devices into existing healthcare systems poses logistical challenges, including the need for healthcare providers to monitor and interpret the data collected [68]. Moreover, while many studies highlight the potential of wearables, there is a need for more rigorous research to validate their effectiveness in diverse populations and clinical settings. Current literature often lacks comprehensive data on the long-term impacts of wearable technology on health outcomes, particularly in pregnant women and those with specific health conditions [16].

- Accuracy and signal quality: Wearable devices often face issues with signal quality and performance variability, which can affect their accuracy in monitoring physiological parameters. For instance, motion artifacts and environmental factors can impact the effectiveness of fetal monitoring devices, leading to unreliable data collection [69].

- Data processing and AI limitations: While AI has shown promise in enhancing pregnancy monitoring, challenges remain in data processing, including the need for robust algorithms that can handle diverse and complex physiological data. The accuracy of AI-based predictions is still a concern, necessitating further research and development [70].

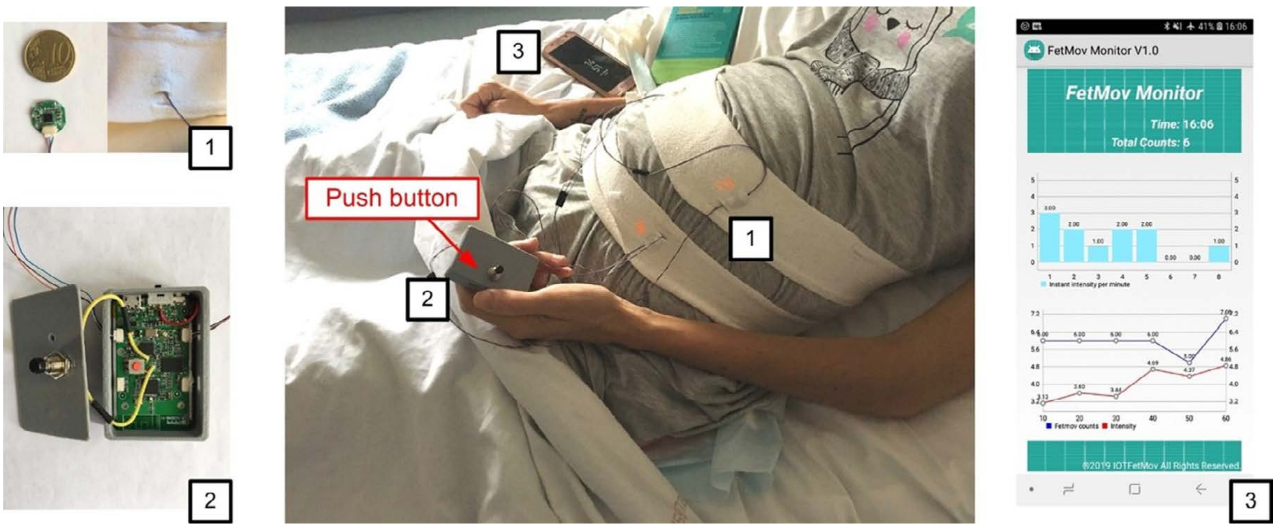


**Figure 2:** The experimental setup for the wearable fetal monitoring system includes: **(1)** A network of four accelerometer sensors. **(2)** A central processing unit housed in a small enclosure, containing a microcontroller, a bluetooth low energy chip for wireless data transmission, and a battery. **(3)** An android device with a graphical user interface for display. For research purposes, the system also incorporates a push button for the mother to log perceived fetal movements [66].

- Data privacy: The collection and storage of sensitive health data by wearable devices raise significant privacy concerns. There is a need for stringent data protection measures to ensure user confidentiality and prevent unauthorized access to personal health information [45, 71].

- Ethical considerations: The use of wearable technology in reproductive health also brings ethical challenges, particularly regarding informed consent and the potential misuse of data. Addressing these ethical issues is essential to build trust among users [45].

- Regulatory gaps: The rapid growth of the femtech market has outpaced existing regulatory frameworks, leading to insufficient oversight and potential risks for users. A comprehensive regulatory approach that incorporates feminist perspectives is necessary to ensure the safety and efficacy of these technologies [71].

- User compliance and acceptance: Despite the potential benefits, user compliance remains a challenge. Factors such as the cost of devices, the complexity of use, and the need for continuous wear can deter users from adopting these technologies. Additionally, there is a need to educate users on the effective use of wearable devices to maximize their benefits [72].

While wearable technology in fertility tracking and pregnancy monitoring faces several challenges, it also offers opportunities for innovation and improvement. The integration of IoT and AI can enhance the capabilities of these devices, providing more accurate and comprehensive monitoring solutions. However, addressing the identified challenges is crucial to ensure that these technologies can be effectively integrated into healthcare systems and widely accepted by users. Continuous advancements in technology, coupled with robust regulatory frameworks and ethical considerations, can help overcome these limitations and improve reproductive health outcomes.

## Future Directions

The future of wearable technology in women's health appears promising, with ongoing advancements in sensor technology and data analytics. As the field evolves, there is a growing emphasis on developing wearables that are not only accurate but also comfortable and aesthetically pleasing to encourage regular use [73]. Furthermore, incorporating user feedback into the design process can enhance engagement and satisfaction among users. Future research should focus on establishing standardized protocols for the use of wearables in clinical practice, ensuring that these devices can be seamlessly integrated into routine healthcare. Additionally, exploring the potential of blockchain technology for securing health data may address privacy concerns and enhance user trust [40].

- Wearable devices are increasingly incorporating multiple sensors to monitor physiological parameters such as heart rate, temperature, and respiratory rate, which are crucial for fertility tracking and pregnancy monitoring [45, 70].

- Future research should focus on developing algorithms that can process data from these sensors in real-time, improving the accuracy of ovulation and fertile window predictions [56].

- The integration of AI and machine learning can enhance the predictive capabilities of these devices, enabling more precise monitoring of pregnancy-related physiological changes [56, 70].

- Understanding consumer perspectives on wearable reproductive health technology is essential for improving user experience and compliance [45].

- Research should address ethical issues related to data privacy and security, ensuring that users' sensitive health information is protected [45, 70].

- Studies should also explore the accessibility and affordability of these technologies to ensure equitable access across different socioeconomic groups [74].

- There is a need for more comprehensive validation studies to confirm the accuracy and reliability of wearable devices in tracking fertility and pregnancy stages [16, 45].

- Clinical trials involving diverse populations can help establish standardized protocols for using these devices in real-world settings [16, 75].

- Research should also focus on the long-term health outcomes associated with the use of wearable technology in reproductive health monitoring [16].

- The IoT offers promising opportunities for remote pregnancy monitoring, allowing continuous data collection and analysis without the need for frequent hospital visits [76].

- Future research should explore the development of IoT-enabled systems that can seamlessly integrate with existing healthcare infrastructure, providing real-time feedback to both users and healthcare providers [76].

- The potential for remote monitoring to reduce healthcare costs and improve maternal and fetal outcomes should be a key area of investigation [75].

- Research should focus on developing cost-effective wearable solutions that can be widely adopted, particularly in low-resource settings [74].

- Innovations in sensor technology and manufacturing processes could help reduce the cost of these devices, making them more accessible to a broader audience [74].

- Studies should also examine the impact of wearable technology on healthcare delivery models, potentially shifting towards more personalized and preventive care approaches [75].

While wearable technology holds great promise for transforming fertility tracking and pregnancy monitoring, it is crucial to address the challenges of data privacy, user compliance, and device validation [77-81]. Additionally, ensuring equitable access to these technologies will be vital in maximizing their potential benefits across diverse populations [82-85]. As research progresses, the integration of advanced sensors, AI, and IoT will likely play a pivotal role in shaping the future of reproductive health monitoring.

## Conclusion

The literature indicates that wearable technology has significantly advanced the monitoring of women's reproductive health, particularly in fertility tracking and pregnancy management. Devices employing physiological signals such as wrist skin temperature, heart rate variability, and respiratory rate consistently demonstrate improved accuracy over traditional calendar or basal body temperature methods for ovulation and fertile window detection. These wearables offer non-invasive, continuous data collection that enhances sensitivity and detection precision, even accommodating irregular menstrual cycles to some extent. However, variability in device performance remains, especially in free-living conditions and among populations with atypical cycle patterns, underscoring the need for further validation and algorithm refinement.

In pregnancy monitoring, wearables integrated with sensors for maternal and fetal vital signs have shown promise for early detection of complications and labor onset, potentially transforming prenatal care through continuous, real-time assessment. The integration of AI and IoT enables sophisticated data processing, personalized risk stratification, and remote alerts, fostering accessibility-particularly in underserved rural and low-resource settings. Nevertheless, challenges such as data completeness, user adherence, and device usability limit consistent effectiveness in free-living environments. The heterogeneity of pregnancy symptoms and physiological responses complicates the interpretation of wearable data, suggesting a need for more individualized analytic approaches.

Accessibility and user acceptability are pivotal concerns. While fertility tracking devices generally enjoy high acceptability and engagement, pregnancy monitoring wearables face compliance hurdles due to comfort issues, device maintenance, and socioeconomic barriers. The digital divide and cost constraints remain significant obstacles to equitable access, especially for marginalized populations. Furthermore, data privacy and ethical considerations are insufficiently addressed across studies, highlighting an urgent need for robust safeguards and inclusive regulatory frameworks that prioritize user trust and equity.

Emerging trends emphasize multimodal sensor fusion, advanced machine learning-particularly personalized n-of-1 models-and wearable designs optimized for continuous, comfortable use. Novel approaches leveraging smartphone-based biosignals and integration with clinical workflows point toward more holistic and scalable solutions. Despite considerable technological progress, many innovations are still in pilot stages without widespread validation or regulatory endorsement. Future research must prioritize large-scale, diverse cohort studies, long-term user engagement strategies, and comprehensive evaluation of health outcomes to realize the full potential of wearable technologies in enhancing women's reproductive health across varied demographic contexts.


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None.


## Conflict of Interest

None.

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