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THE ROLE OF WEARABLE DIGITAL TECHNOLOGIES IN REPRODUCTIVE HEALTH MONITORING: A REVIEW OF CLINICAL EVIDENCE AND TECHNOLOGICAL LIMITATIONS

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ABSTRACT

Wearable digital technologies are increasingly being used for reproductive health monitoring and may offer an alternative to traditional fertility awareness methods. This review aimed to evaluate the clinical utility, accuracy, and limitations of wearable devices for menstrual cycle tracking and fertile window detection.

A structured review of recent literature was conducted, focusing on studies assessing wearable digital technologies that measure physiological parameters such as body temperature, heart rate, and other related signals across the menstrual cycle. Particular attention was given to their ability to detect ovulation and predict the fertile window compared with established methods.

The findings indicate that wearable digital technologies can reliably capture cyclical physiological changes associated with menstrual phases. Continuous monitoring, particularly of temperature and cardiovascular parameters, appears to improve sensitivity compared with single-point measurements. Multimodal approaches that combine several physiological signals further enhance predictive performance. Wearable digital technologies generally outperform calendar-based methods and show comparable accuracy to some hormone-based approaches. However, most devices identify a narrower fertile window than the biologically defined period, which may limit their effectiveness for both conception planning and contraception.

Despite their promise, significant limitations remain, including variability in study design, lack of standardized validation methods, and reduced accuracy in individuals with irregular cycles. User adherence and external factors may also affect data quality and interpretation.

In conclusion, wearable digital technologies represent a promising tool for personalized reproductive health monitoring, but further high-quality studies and technological refinement are required before they can be fully integrated into clinical practice.

KEYWORDS

Wearable Digital Technologies, Reproductive Health, Fertility Tracking, Menstrual Cycle, Ovulation Prediction, Digital Health

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1. Introduction

Fertility, defined as the ability to achieve a clinical pregnancy, is a fundamental component of reproductive health and remains a growing global concern. It is estimated that over 186 million women of reproductive age worldwide are affected by infertility, with declining fertility rates observed in many populations (Cao et al., 2024). Female fertility is influenced by multiple factors, including age, endocrine function, lifestyle, and gynecological conditions such as polycystic ovary syndrome, endometriosis, and uterine fibroids. Menstrual cycle characteristics, particularly regularity and ovulation patterns, serve as important indicators of reproductive health and fertility potential.

The menstrual cycle is a dynamic physiological process regulated by complex hormonal interactions, typically lasting 28–30 days but demonstrating considerable inter- and intra-individual variability. It consists of the follicular phase, ovulation, and the luteal phase, each associated with distinct hormonal and physiological changes. The fertile window, defined as the five days preceding ovulation and the day of ovulation, represents the period with the highest probability of conception. Accurate identification of this window is critical for both achieving and avoiding pregnancy, as well as for broader reproductive health monitoring (Wilcox et al., 1995).

Historically, fertility awareness-based (FAB) methods have been used to estimate the fertile window by tracking physiological signs such as basal body temperature (BBT), cervical mucus, and menstrual cycle timing. These methods rely heavily on user interpretation and adherence, and while they can be effective, they present several limitations. For example, BBT exhibits a biphasic pattern due to progesterone increase after ovulation; however, it primarily allows retrospective confirmation of ovulation rather than prospective prediction of the fertile window (Yu et al., 2022). Similarly, calendar-based methods fail to account for natural variability in cycle length, and cervical mucus assessment is inherently subjective.

The development of wearable digital technologies (WDTs) has led to the widespread adoption of smartphone applications for menstrual cycle tracking. These tools aim to simplify fertility awareness by integrating user-reported data such as menstruation dates, symptoms, and temperature measurements. However, their accuracy remains inconsistent, largely due to reliance on manual data entry, recall bias, and algorithmic limitations. Studies have shown significant discrepancies between predicted and actual cycle events, raising concerns about their reliability and clinical utility (Lyzwinski et al., 2024).

In response to these limitations, wearable digital technologies have emerged as a promising advancement in reproductive health monitoring. WDTs enable continuous, non-invasive collection of physiological parameters, including skin or core body temperature, heart rate (HR), heart rate variability (HRV), respiratory rate, and sleep patterns. These parameters are known to fluctuate across the menstrual cycle in response to hormonal changes, providing a physiological basis for cycle tracking. Continuous monitoring offers a significant advantage over traditional single-point measurements by capturing circadian and cycle-related variations in real time (Goodale et al., 2019; Moghimikandelousi et al., 2025).

Recent studies suggest that integrating multiple physiological signals, often combined with machine learning algorithms, may improve the accuracy of ovulation and fertile window prediction compared to traditional methods based on single parameters. For instance, wearable devices measuring temperature and cardiovascular parameters have demonstrated the potential to detect cycle phases and predict fertile windows with greater precision. Additionally, novel devices such as intravaginal sensors enable continuous core body temperature monitoring, offering high-resolution data that may further enhance cycle characterization (Regidor et al., 2018).

Despite these technological advances, important challenges remain. Questions persist regarding the accuracy, standardization, and generalizability of wearable-based fertility monitoring across diverse populations, particularly among women with irregular cycles. Furthermore, many studies lack gold-standard validation using hormonal assays or ultrasound-confirmed ovulation, limiting the interpretability of findings. Variability in measurement protocols, device types and analytical methods further complicates comparisons across studies (de Jager et al., 2026).

Given the rapid evolution of wearable technologies and their increasing integration into healthcare, there is a growing need to critically evaluate their clinical applicability, accuracy and limitations in reproductive health monitoring. This review aims to synthesize current evidence on WDTs for fertility tracking, with a focus on their clinical applications, technological performance, and future directions in personalized reproductive medicine.

2. Methodology

2.1 Search strategy

This review was conducted following a structured literature search strategy. A comprehensive literature search was performed to identify studies evaluating wearable devices for reproductive health monitoring and fertility tracking.

Electronic databases including PubMed and MEDLINE were searched for relevant studies published up to 2026. The search strategy combined keywords related to wearable technology and reproductive health, including terms such as “wearable digital technologies”, “fertility tracking”, “menstrual cycle”, “ovulation prediction”, “basal body temperature”, “heart rate variability” and “digital health”. Reference lists of selected articles were also screened to identify additional relevant studies.

2.2 Eligibility Criteria

Studies were included if they met the following criteria:

- evaluated wearable devices or digital technologies for menstrual cycle tracking or fertility monitoring,
- assessed physiological parameters such as body temperature, heart rate, or heart rate variability,
- involved women of reproductive age,
- were original research articles, systematic reviews, or clinical studies published in English.

Studies were excluded if they:

- did not involve wearable or digital monitoring technologies,
- focused solely on non-human subjects,
- lacked relevant outcomes related to fertility or menstrual cycle tracking,
- were conference abstracts, editorials, or non-peer-reviewed sources.

2.3 Study selection

All identified records were screened based on title and abstract. Full texts of potentially relevant studies were then assessed for eligibility. Studies that met the inclusion criteria were included in the final analysis. Duplicates were removed prior to screening. The final selection included studies that met all predefined criteria.

2.4 Data extraction

Relevant data were extracted from each included study, including study design, population characteristics, type of WDTs, physiological parameters measured and reported outcomes related to ovulation detection or fertile window prediction.

2.5 Data synthesis

A qualitative synthesis of the included studies was conducted. The results were analyzed to compare the performance of WDTs with traditional fertility awareness methods, focusing on accuracy, clinical applicability and technological limitations.

3. Physiology of the Menstrual Cycle

The menstrual cycle is a highly coordinated physiological process regulated by the hypothalamic-pituitary-ovarian axis (HPO), integrating signals from the hypothalamus, anterior pituitary, ovaries, and uterus. Its primary function is to prepare the female body for ovulation and potential pregnancy through cyclic hormonal fluctuations and structural changes in the endometrium (Thiyagarajan et al., 2024). Clinically, the first day of menstrual bleeding is defined as day 1 of the cycle, and a normal cycle typically occurs every 24–38 days with bleeding lasting ≤8 days (Thiyagarajan et al., 2024).

Hormonal Regulation and Feedback Mechanisms

At the core of menstrual physiology lies a tightly controlled hormonal feedback system. Pulsatile secretion of gonadotropin-releasing hormone from the hypothalamus stimulates the anterior pituitary to release follicle-stimulating hormone and luteinizing hormone. These gonadotropins act on the ovaries, where follicular cells produce sex steroids, primarily estradiol and progesterone (Thiyagarajan et al., 2024).

During most of the cycle, estradiol and progesterone exert negative feedback on the hypothalamus and pituitary, regulating FSH and LH secretion. However, a key physiological shift occurs in the late follicular phase, when sustained high levels of estradiol trigger a positive feedback mechanism, resulting in the mid-cycle LH surge that induces ovulation (Thiyagarajan et al., 2024).

Ovarian and Endometrial Cycles

The menstrual cycle consists of two interrelated cycles: the ovarian cycle (follicular phase, ovulation, luteal phase) and the endometrial cycle (menstrual, proliferative, and secretory phases). These processes are synchronized through hormonal signaling (Thiyagarajan et al., 2024).

Follicular and proliferative phases:

The follicular phase begins on day 1 of menstruation and is characterized by FSH-driven maturation of ovarian follicles. A dominant follicle emerges, producing increasing amounts of estradiol. This hormone stimulates proliferation of the endometrium, thickening the uterine lining and enhancing vascularization. Estradiol also modifies cervical mucus, making it more permeable to sperm, thereby facilitating fertilization (Thiyagarajan et al., 2024).

Ovulation:

Ovulation occurs approximately 36–44 hours after the LH surge, typically around 14 days before the next menstruation in a regular cycle. The rupture of the dominant follicle releases the oocyte into the fallopian tube (Thiyagarajan et al., 2024). This event defines the transition from the follicular to the luteal phase and corresponds to the most fertile period of the cycle (Yu et al., 2022).

Luteal and secretory phases:

Following ovulation, the corpus luteum forms and secretes progesterone, the dominant hormone of this phase. Progesterone transforms the proliferative endometrium into a secretory lining capable of supporting embryo implantation. It also increases basal body temperature and thickens cervical mucus, reducing further sperm penetration (Thiyagarajan et al., 2024). If fertilization does not occur, progesterone and estradiol levels decline, leading to endometrial shedding and the onset of menstruation (Thiyagarajan et al., 2024).

Hormonal Dynamics Across the Cycle

The cyclical fluctuations of estradiol, progesterone, LH, and FSH are central to menstrual physiology and fertility. Estradiol rises progressively during the follicular phase, peaks prior to ovulation, and then declines. The LH surge represents a sharp, transient increase triggering ovulation, while progesterone rises during the luteal phase (Thiyagarajan et al., 2024).

These hormonal dynamics also generate measurable physiological changes. For instance, basal body temperature increases by approximately 0.3–0.7°C after ovulation due to progesterone (Shi et al., 2026). However, temperature-based methods mainly confirm ovulation retrospectively rather than predict it accurately (Yu et al., 2022).

Physiological Variability and Pathophysiology

Despite its structured nature, the menstrual cycle exhibits inter- and intra-individual variability. Irregular cycles may reflect disruptions in the HPO axis and are associated with endocrine disorders such as polycystic ovary syndrome, thyroid dysfunction, or hyperprolactinemia (Thiyagarajan et al., 2024).

Anovulatory cycles represent a key pathological variation in which ovulation does not occur, resulting in the absence of progesterone production. This leads to unopposed estrogen stimulation of the endometrium and irregular bleeding patterns (Thiyagarajan et al., 2024).

Abnormal uterine bleeding may arise from structural or non-structural causes and highlights the importance of hormonal balance for normal reproductive function (Thiyagarajan et al., 2024).

Clinical Relevance of Hormonal Physiology

Understanding the hormonal physiology of the menstrual cycle is fundamental for interpreting fertility patterns and reproductive outcomes. Subtle variations in menstrual characteristics—such as cycle length or timing of ovulation—may be associated with altered fertility potential, although evidence remains inconsistent (Cao et al., 2024).

From a clinical perspective, precise knowledge of hormonal dynamics enables better assessment of ovulatory function and supports modern approaches to fertility monitoring, including wearable technologies that track physiological changes associated with hormonal fluctuations (Shi et al., 2026).

4. Clinical Application

Fertility monitoring and optimization of conception

Accurate identification of the fertile window remains a central challenge in reproductive medicine and a key determinant of successful conception. Approximately 15% of women of reproductive age actively attempt pregnancy, yet many experience difficulties primarily due to incorrect timing of intercourse relative to ovulation (Niggli et al., 2023). The fertile window, defined as the five days preceding ovulation and the day of ovulation itself, represents the period of highest conception probability, with peak fertility occurring shortly before ovulation (Shi et al., 2026). However, most women lack precise awareness of this window, and substantial inter- and intra-individual variability in ovulation timing further complicates its prediction (Niggli et al., 2023; Shi et al., 2026).

Traditional methods for fertility tracking, including calendar-based approaches, basal body temperature (BBT) monitoring, and urinary luteinizing hormone (LH) testing, present important limitations. Calendar-based methods fail to account for cycle variability, while BBT primarily confirms ovulation retrospectively due to progesterone-driven thermogenic changes occurring after ovulation (Zhu et al., 2021; Niggli et al., 2023). LH tests, although correlated with ovulation, detect only the late pre-ovulatory phase and may miss earlier days of high fertility (Niggli et al., 2023). Furthermore, fertility awareness-based methods require high user compliance and are susceptible to reporting errors and lifestyle-related confounders (Li et al., 2025).

Wearable digital technologies have emerged as a promising solution to these limitations by enabling continuous, real-time, and non-invasive monitoring of physiological parameters associated with hormonal fluctuations. These devices collect high-resolution longitudinal data on temperature, heart rate (HR), heart rate variability (HRV), respiratory rate, and sleep patterns under real-life conditions, allowing for more precise and individualized fertility tracking (Shi et al., 2026; Moghimikandelousi et al., 2025). Unlike traditional single-point measurements, wearable sensors generate millions of data points across the menstrual cycle, capturing subtle physiological dynamics that are critical for accurate prediction of the fertile window (Goodale et al., 2019; Lyzwinski et al., 2024).

Clinical evidence indicates that wearable-based approaches outperform traditional methods. A recent meta-analysis reported a pooled accuracy of 0.88 for fertility window detection using wearable devices, compared with 0.75 for BBT and 0.72 for calendar-based methods (Shi et al., 2026). Importantly, WDTs demonstrate improved sensitivity and specificity, supporting their clinical utility in optimizing conception timing (Shi et al., 2026; Lyzwinski et al., 2024).

Physiological biomarkers and ovulation detection

Wearable devices leverage multiple physiological biomarkers that reflect hormonal fluctuations across the menstrual cycle. Among these, body temperature remains a cornerstone parameter. Progesterone induces a thermogenic effect following ovulation, leading to a biphasic temperature pattern with an increase of approximately 0.3–0.7°C in the luteal phase (Shi et al., 2026; Zhu et al., 2021).

Continuous temperature monitoring using WDTs, particularly wrist skin temperature or intravaginal sensors, has demonstrated improved sensitivity compared with traditional oral BBT measurements. Wrist skin temperature closely mirrors BBT patterns while providing more stable and continuous recordings, particularly during sleep when external confounders are minimized (Zhu et al., 2021; Moghimikandelousi et al., 2025). Intravaginal sensors offer even greater accuracy by measuring core body temperature continuously, although their invasiveness may limit widespread adoption (Moghimikandelousi et al., 2025).

In addition to temperature, cardiovascular parameters provide valuable insights into menstrual cycle physiology. Heart rate increases during the fertile window and luteal phase, while HRV decreases, reflecting reduced parasympathetic activity under the influence of progesterone (Shilaih et al., 2017; de Jager et al., 2026). Wearable photoplethysmography (PPG) enables continuous monitoring of these parameters in real-world settings, overcoming the limitations of clinic-based measurements (Shilaih et al., 2017).

Other physiological signals, including respiratory rate, skin perfusion, and sleep patterns, also exhibit phase-dependent variation, further supporting their role as digital biomarkers of fertility (Lyzwinski et al., 2024). Importantly, the fertile window often represents a physiological "inflection point," during which multiple parameters—temperature, HR, and HRV—simultaneously change, enhancing detectability when analyzed collectively (Yu et al., 2022; Shilaih et al., 2017).

Multi-parameter models and machine learning in fertility prediction

A key advantage of WDTs lies in their ability to integrate multiple physiological signals into predictive models. Multi-parameter approaches combining temperature, HR, HRV, and other signals consistently outperform single-parameter methods such as BBT alone (Shi et al., 2026; Yu et al., 2022).

Machine learning algorithms play a central role in analyzing complex time-series data generated by wearable devices. Advanced computational models, including random forests and support vector machines, enable the identification of individualized physiological patterns and improve prediction accuracy (Shi et al., 2026; Lyzwinski et al., 2024). Studies have demonstrated that wearable-based algorithms can detect the fertile window with high accuracy, in some cases exceeding 90%, and outperform conventional smartphone applications (Goodale et al., 2019; Lyzwinski et al., 2024).

For example, integration of HR data with BBT significantly improves predictive performance compared with temperature-only models, highlighting the importance of multimodal data integration (Yu et al., 2022). Similarly, wearable-based algorithms have achieved high specificity and sensitivity in identifying fertile periods, enabling more precise timing of intercourse and improved chances of conception.

However, it is important to note that WDTs typically estimate a time interval surrounding ovulation rather than the exact ovulation day. Detection accuracy is highest within a ±2–3-day window around ovulation, which is clinically relevant given the biological definition of the fertile window (Shi et al., 2026).

Device heterogeneity and user-centered considerations

Wearable devices used for fertility monitoring vary considerably in design, including wristbands, rings, vaginal sensors, ear-worn devices, and armbands. Each modality presents trade-offs between accuracy, usability and user acceptability.

Wrist-worn devices and rings offer high compliance and convenience but may be affected by movement and environmental factors. In contrast, vaginal sensors provide more precise core temperature measurements but are associated with invasiveness and lower acceptability (Li et al., 2025). Ear-worn and armband devices offer alternative approaches but may suffer from data loss or lower adherence (Li et al., 2025).

These differences highlight the importance of balancing measurement accuracy with user comfort and long-term adherence, which are critical for effective fertility monitoring in real-world settings.

Clinical relevance for reproductive outcomes

Beyond ovulation detection, WDTs enable longitudinal assessment of menstrual cycle characteristics that are associated with reproductive outcomes. Variations in menstrual cycle length, bleeding duration and age at menarche have been linked to fertility and miscarriage risk (Cao et al., 2024, Xiping et al., 2022).

Continuous monitoring allows for early identification of irregular cycles and anovulatory patterns, which occur in up to 12–37% of cycles and may go undetected using traditional methods (Shilaih et al., 2017). This may facilitate earlier clinical evaluation and intervention in individuals with underlying reproductive disorders.

Secondary clinical applications of wearable digital technologies

Beyond fertility monitoring, wearable technologies have broader applications in reproductive health. Continuous tracking of physiological parameters may improve menstrual cycle awareness, support early detection of irregularities and enhance patient engagement in reproductive health management (Moghimikandelousi et al., 2025).

Emerging innovations, such as bioengineered wearable sensors capable of detecting hormonal biomarkers (e.g., estradiol, progesterone metabolites) through sweat-based nanobiosensors, offer promising avenues for integrating biochemical data with physiological monitoring (Moghimikandelousi et al., 2025).

Additionally, wearable-derived data may support early identification of conditions such as polycystic ovary syndrome or endometriosis and contribute to personalized healthcare strategies. However, these applications remain in early stages of development and require further validation (Lyzwinski et al., 2024; Moghimikandelousi et al., 2025).

5. Accuracy and limitations

The accuracy of wearable devices for reproductive health monitoring depends largely on the type, number, and quality of physiological parameters measured, as well as the methodological approaches used for data collection and analysis. Compared with traditional fertility awareness-based methods, WDTs offer continuous, high-resolution data, which may improve the detection of subtle physiological changes across the menstrual cycle. However, their performance remains variable and is influenced by both biological and technical factors.

Temperature-based monitoring remains one of the most extensively studied approaches. Continuous measurements of skin or core body temperature have demonstrated the ability to capture cyclical variations associated with hormonal changes. For instance, nocturnal finger skin temperature and oral temperature differ significantly between the follicular and luteal phases, with skin temperature showing a greater between-phase change (Maijala et al., 2019). Similarly, core body temperature follows circadian and circamensual rhythms, with higher mean values during the luteal phase and a nadir preceding the luteinizing hormone (LH) surge. Continuous intravaginal temperature monitoring has shown particularly promising results, with reported accuracy of up to 88.8% in identifying a periovulatory window spanning several days (Regidor et al., 2018).

Importantly, continuous temperature monitoring appears to outperform traditional basal body temperature (BBT) measurements. Wrist skin temperature, in particular, has demonstrated higher sensitivity in detecting ovulation-related temperature shifts compared to oral BBT, likely due to its ability to capture continuous nocturnal data and reduce the influence of circadian variability (Zhu et al., 2021). Unlike single-point BBT measurements, which are highly dependent on strict timing and user compliance, continuous measurements provide a more stable representation of thermophysiological patterns. However, this increased sensitivity may come at the cost of lower specificity, reflecting a common trade-off in diagnostic testing. Consequently, while continuous temperature monitoring may be useful for maximizing conception probability, it is insufficient as a standalone method for preventing unintended pregnancy due to limited negative predictive value.

Beyond temperature, wearable devices increasingly incorporate additional physiological parameters such as heart rate (HR), heart rate variability (HRV), and respiratory rate. The integration of multiple signals, often analyzed using machine learning algorithms, has shown potential to improve predictive accuracy. For example, models combining BBT and HR data have demonstrated the feasibility of predicting both ovulation and menstruation; however, their performance is still constrained by the limited number of input variables and reliance on user-reported measurements (Yu et al., 2022). Expanding the range of monitored parameters and enabling fully passive data collection through wearable sensors may enhance both accuracy and usability.

Despite these advances, several limitations significantly affect the reliability and generalizability of wearable-based fertility tracking. One major challenge is methodological heterogeneity across studies. Differences in device types (e.g., electrocardiography vs photoplethysmography), measurement sites, recording durations, and analytical methods hinder direct comparisons and limit the ability to synthesize findings across studies (de Jager et al., 2026). In particular, shorter recording intervals and motion artifacts in WDTs may reduce signal accuracy, especially for HRV measurements.

Another critical limitation relates to the classification of menstrual cycle phases. Many studies rely on self-reported cycle data or calendar-based estimations rather than biochemical verification (e.g., hormonal assays or ultrasound-confirmed ovulation). This can lead to misclassification of cycle phases and inconsistent findings, particularly when evaluating physiological markers such as HRV that are sensitive to hormonal fluctuations (de Jager et al., 2026). As a result, the physiological validity of wearable-derived measurements remains uncertain in some contexts.

User behavior and compliance also play a significant role in data quality. Traditional approaches requiring manual input, such as daily BBT measurement or symptom logging, are prone to missing data and reporting bias. Even in studies using WDTs, substantial proportions of data may be excluded due to incomplete recordings, raising concerns about real-world adherence (Zhu et al., 2021). Additionally, factors such as sleep patterns, physical activity, alcohol consumption and environmental conditions can influence physiological signals, further complicating interpretation.

Population characteristics represent another important limitation. Many studies have been conducted in relatively homogeneous groups, often consisting of young, healthy women with regular menstrual cycles. This limits the generalizability of findings to broader populations, including women with irregular cycles, underlying health conditions, or diverse demographic backgrounds. Furthermore, wearable digital technologies may perform differently across these groups, particularly in the presence of hormonal variability or disrupted circadian rhythms.

Finally, although WDTs provide continuous and non-invasive monitoring, their accuracy is still generally inferior to gold-standard methods such as transvaginal ultrasonography or hormonal assays. While wearables offer a practical and scalable alternative for long-term monitoring, their current role should be considered complementary rather than definitive in clinical settings.

In summary, wearable devices represent a promising advancement in fertility tracking, offering improved sensitivity and continuous data collection compared to traditional methods. However, their accuracy is influenced by multiple factors, including measurement techniques, algorithm design, user behavior and study methodology. Addressing these limitations through standardized protocols, multimodal data integration and rigorous clinical validation will be essential for their broader implementation in reproductive health care.

6. Future perspectives

The rapid evolution of WDTs for reproductive health monitoring highlights their potential to transform fertility care into a more personalized, data-driven, and proactive field. However, further advancements in technology, methodology and clinical validation are required to fully realize their clinical utility.

One of the most important future directions involves the integration of multimodal physiological data. Current wearable systems often rely on a limited number of parameters, such as temperature or heart rate, which restricts predictive performance. Expanding data collection to include additional biomarkers—such as heart rate variability (HRV), respiratory rate, and hormonal indicators—may significantly improve the accuracy of menstrual phase detection and fertile window prediction (Yu et al., 2022; de Jager et al., 2026). Importantly, combining physiological monitoring with biochemical validation, including urinary luteinizing hormone (LH) testing and serum hormone measurements, has been proposed as a key strategy to improve the accuracy and standardization of menstrual cycle assessment (de Jager et al., 2026).

Future research should also prioritize methodological standardization. The lack of consistent definitions for menstrual cycle phases, variability in device types and differences in data collection protocols currently limit comparability across studies. The adoption of standardized classification frameworks and harmonized measurement protocols would enable more robust comparisons and facilitate meta-analyses (de Jager et al., 2026). In addition, longitudinal studies spanning different reproductive stages—including adolescence, reproductive age and menopause—are needed to better understand individual variability and hormonal dynamics over time.

Another critical area for future development is user-centered design and real-world applicability. Despite technological advances, relatively little is known about user experience, long-term adherence and acceptability of wearable devices for fertility monitoring. Factors such as comfort, usability and perceived value may significantly influence adherence and data quality (Lyzwinski et al., 2024). Furthermore, privacy and ethical concerns related to the collection and storage of sensitive reproductive health data must be addressed to ensure user trust and widespread adoption. Secure data governance frameworks and transparent data usage policies will be essential, particularly in sociopolitical contexts where reproductive data privacy is of heightened concern.

Importantly, future studies should focus on high-quality clinical validation. There is a clear need for large-scale, prospective trials comparing WDTs with gold-standard methods such as ultrasonography and hormonal assays. Such studies should evaluate not only the accuracy of ovulation detection but also clinically meaningful outcomes, including time to pregnancy and effectiveness in preventing unintended pregnancies (Lyzwinski et al., 2024). Expanding research to include diverse populations, particularly women with irregular cycles or underlying health conditions, will be crucial for improving generalizability.

Technological innovation is expected to further enhance wearable systems. The next generation of devices will likely incorporate wireless connectivity, real-time feedback and seamless integration with digital health platforms. These advancements may enable continuous remote monitoring and facilitate early detection of reproductive health abnormalities, shifting care from reactive to preventive models (Moghimikandelousi et al., 2025). Ultimately, wearable digital technologies have the potential to bridge the gap between high-accuracy clinical diagnostics and accessible, everyday health monitoring.

Artificial intelligence in reproductive health monitoring

Artificial intelligence (AI) represents a key driver of future advancements in wearable-based fertility monitoring. At its core, AI—particularly machine learning—enables the analysis of large, complex datasets to identify patterns that may not be detectable through traditional statistical approaches. In the context of WDTs, AI algorithms can integrate continuous physiological data streams to improve the prediction of ovulation, menstrual phases and fertility windows (Moghimikandelousi et al., 2025; Wu et al., 2025).

The incorporation of AI into wearable systems offers several advantages. First, it enables personalized predictions by adapting to individual physiological patterns rather than relying on population-based averages. This is particularly important given the high inter- and intra-individual variability in menstrual cycles. Second, AI can reduce user-related errors by automating data interpretation, minimizing reliance on manual input and subjective assessment (Moghimikandelousi et al., 2025). Third, AI-driven models can continuously improve over time through iterative learning, enhancing their predictive accuracy as more data become available.

Beyond fertility tracking, AI has broader applications in reproductive medicine. In assisted reproductive technologies (ART), machine learning models have been developed to support embryo selection, predict implantation success, and optimize treatment protocols, demonstrating high predictive performance in some experimental settings (Zaninovic et al., 2019; Wu et al., 2025). These approaches highlight the potential of AI to support clinical decision-making and advance precision medicine in reproductive health.

However, several challenges must be addressed before AI can be fully integrated into clinical practice. High-quality, large-scale datasets are required to train robust and generalizable models, yet such data are often difficult to obtain due to privacy concerns and variability in data collection. Additionally, many AI-based tools lack prospective clinical validation, limiting their current applicability. Ethical considerations—including data security, algorithm transparency and potential biases—also remain critical issues.

Despite these challenges, the integration of AI with wearable digital technologies is expected to play a transformative role in reproductive health. By enabling real-time, personalized and predictive monitoring, AI-driven systems may shift fertility care toward a more proactive and individualized model, ultimately improving clinical outcomes and patient empowerment.

7. Discussion

This review synthesizes current evidence on wearable devices for reproductive health monitoring, highlighting their emerging clinical potential alongside important methodological and technological limitations. Overall, the findings suggest that WDTs represent a promising advancement over traditional fertility awareness-based methods, particularly due to their ability to provide continuous, non-invasive and personalized monitoring of physiological parameters across the menstrual cycle.

Across the included studies, wearable devices consistently demonstrated the ability to detect cyclical physiological changes, particularly in temperature and cardiovascular parameters such as heart rate (HR) and heart rate variability (HRV). These findings align with established knowledge on hormonal regulation of thermoregulation and autonomic function throughout the menstrual cycle. Continuous measurements—

especially nocturnal skin temperature—appear to offer improved sensitivity compared to traditional basal body temperature (BBT) methods, largely due to reduced susceptibility to circadian variability and user-dependent measurement errors. Moreover, the integration of multiple physiological signals has been shown to enhance predictive performance, supporting the concept that multimodal monitoring is superior to single-parameter approaches (Shi et al., 2026; Yu et al., 2022).

Importantly, WDTs appear to outperform traditional calendar-based methods and self-reported BBT in terms of accuracy and usability. Compared to calendar methods, which are limited by inter- and intra-individual cycle variability and recall bias, WDTs provide real-time physiological data that enable more individualized predictions (Shi et al., 2026). In addition, wearable-based approaches may be particularly beneficial for individuals with irregular cycles, for whom prediction based solely on past cycle data is unreliable. However, despite these advantages, current wearable devices typically predict a fertile window within approximately ±3 days of ovulation, which does not fully align with the biological fertile window spanning up to 5 days before ovulation and 24 hours after. This discrepancy represents a clinically relevant limitation, particularly for both pregnancy planning and contraception.

From a clinical perspective, WDTs have applications beyond fertility tracking. Accurate prediction of menstrual phases may support the management of conditions such as premenstrual dysphoric disorder and dysmenorrhea, enabling individuals to anticipate symptoms and plan daily activities accordingly (Lyzwinski et al., 2024). Furthermore, continuous monitoring of physiological parameters may provide early indicators of reproductive health disturbances, potentially supporting earlier diagnosis and intervention.

Despite these promising findings, several limitations must be considered. First, substantial heterogeneity exists across studies in terms of device type, physiological parameters measured, and algorithmic approaches. This variability limits direct comparability and contributes to uncertainty in the overall estimates of accuracy. Second, many studies rely on indirect methods for ovulation confirmation, such as LH testing or calendar estimation, rather than gold-standard ultrasonography, which may affect the validity of reported outcomes (Shi et al., 2026). Third, small sample sizes and the predominance of observational or pilot study designs reduce the robustness and generalizability of the evidence.

User-related factors also play a critical role in real-world performance. Although wearable devices reduce reliance on manual data entry, adherence to device use and synchronization remains essential for maintaining data quality. Studies have demonstrated that missing data can significantly reduce predictive accuracy, although some algorithms may retain reasonable performance even with partial data loss (Goodale et al., 2019). Additionally, external factors such as illness, stress, sleep disruption, and environmental conditions may influence physiological signals, potentially confounding interpretation.

Another important consideration is the trade-off between accuracy and user comfort. While intravaginal devices provide more direct measurements of core body temperature and may achieve higher accuracy, they may be less acceptable for long-term use compared to non-invasive wrist- or finger-worn devices (Lyzwinski et al., 2024). Therefore, user-centered design remains essential for optimizing both adherence and clinical effectiveness.

Finally, concerns regarding the commercialization of fertility tracking technologies should be acknowledged. The increasing availability of consumer-targeted applications without sufficient clinical validation raises potential risks, including unintended pregnancies due to inaccurate predictions. This underscores the need for rigorous efficacy studies and regulatory oversight prior to widespread implementation.

Taken together, the current evidence supports the potential of wearable devices as valuable tools for reproductive health monitoring. However, their clinical application should be approached with caution until further high-quality evidence becomes available. Future research should prioritize standardized methodologies, large-scale prospective studies, and integration with biochemical validation to improve both accuracy and clinical relevance.

8. Conclusions

Wearable digital technologies represent a rapidly evolving and promising approach to menstrual cycle and fertility monitoring, offering continuous, non-invasive and personalized assessment of physiological parameters. Compared to traditional methods, they demonstrate improved sensitivity and usability, particularly when integrating multiple physiological signals and advanced analytical approaches.

However, current wearable digital technologies remain limited by variability in accuracy, incomplete alignment with the biological fertile window and a lack of robust clinical validation. Methodological heterogeneity, reliance on indirect ovulation markers and limited data in diverse populations further constrain their clinical applicability.

The integration of multimodal physiological data, standardized research protocols and advanced analytical techniques—including artificial intelligence—has the potential to significantly enhance the accuracy and utility of these systems. With further development and validation, WDTs may play an important role in personalized reproductive health care, supporting both pregnancy planning and contraception, as well as broader gynecological health monitoring.

At present, wearable devices should be considered complementary tools rather than standalone diagnostic methods. Continued research and careful clinical implementation will be essential to fully realize their potential in reproductive medicine.

These technologies have the potential to reshape reproductive health care by enabling more accessible, individualized and data-driven approaches to fertility monitoring.

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REFERENCES

1. Ali, Z. E., Ammar, O. F., Liperis, G., Sharma, K., Hall, J., Grace, B., & Fraire-Zamora, J. J. (2025). Wearable intelligence: Can we transform fertility tracking through digital innovation? *Human Reproduction, 40*(9), 1803–1806. https://doi.org/10.1093/humrep/deaf148
2. Cao, Y., Zhao, X., Dou, Z., Gong, Z., Wang, B., & Xia, T. (2024). The correlation between menstrual characteristics and fertility in women of reproductive age: A systematic review and meta-analysis. *Fertility and Sterility, 122*(5), 918–927. https://doi.org/10.1016/j.fertnstert.2024.06.016
3. de Jager, E., Caulfield, B., Angelidi, E., MacNamee, B., & Holden, S. (2026). Wearable-derived heart rate variability across the menstrual cycle, hormonal contraceptive use, and reproductive life stages in females: A living systematic review. *Sports Medicine*. https://doi.org/10.1007/s40279-025-02388-y
4. Goodale, B. M., Shilaih, M., Falco, L., Dammeier, F., Hamvas, G., & Leeners, B. (2019). Wearable sensors reveal menses-driven changes in physiology and enable prediction of the fertile window: Observational study. *Journal of Medical Internet Research, 21*(4), e13404. https://doi.org/10.2196/13404
5. Li, Y., Fang, Y., & Gu, S. (2025). Effectiveness of menstruation and fertility tracking technology in childbearing women: A scoping review. *Revista da Escola de Enfermagem da USP, 59*, e20240454. https://doi.org/10.1590/1980-220X-REEUSP-2024-0454en
6. Lyzwinski, L., Elgendi, M., & Menon, C. (2024). Innovative approaches to menstruation and fertility tracking using wearable reproductive health technology: Systematic review. *Journal of Medical Internet Research, 26*, e45139. https://doi.org/10.2196/45139
7. Moghimikandelousi, S., Najm, L., Lee, Y., Bayat, F., Prasad, A., Khan, S., Bhavan, A., Gao, W., Hosseinidoust, Z., & Didar, T. F. (2025). Advances in biomonitoring technologies for women's health. *Nature Communications, 16*(1), 8507. https://doi.org/10.1038/s41467-025-63501-3
8. Niggli, A., Rothenbühler, M., Sachs, M., & Leeners, B. (2023). Can wrist-worn medical devices correctly identify ovulation? *Sensors, 23*(24), 9730. https://doi.org/10.3390/s23249730
9. Regidor, P.-A., Kaczmarczyk, M., Schiweck, E., Goeckenjan-Festag, M., & Alexander, H. (2018). Identification and prediction of the fertile window with a new web-based medical device using a vaginal biosensor for measuring the circadian and circamensual core body temperature. *Gynecological Endocrinology, 34*(3), 256–260. https://doi.org/10.1080/09513590.2017.1390737
10. Shi, Y., Wang, C. C., Yang, Y., Li, Q., Chung, P. W., & Wang, Y. (2026). The diagnostic accuracy of wearable digital technology in detecting fertility window and menstrual cycles: A systematic review and Bayesian network meta-analysis. *NPJ Digital Medicine, 9*(1), 139. https://doi.org/10.1038/s41746-025-02320-8

11. Shilaih, M., de Clerck, V., Falco, L., Kübler, F., & Leeners, B. (2017). Pulse rate measurement during sleep using wearable sensors and its correlation with the menstrual cycle phases: A prospective observational study. *Scientific Reports, 7*(1), 1294. https://doi.org/10.1038/s41598-017-01433-9
12. Shilaih, M., Goodale, B. M., Falco, L., Kübler, F., de Clerck, V., & Leeners, B. (2018). Modern fertility awareness methods: Wrist wearables capture the changes in temperature associated with the menstrual cycle. *Bioscience Reports, 38*(6), BSR20171279. https://doi.org/10.1042/BSR20171279
13. Thiyagarajan, D. K., Basit, H., & Jeanmonod, R. (2026). Physiology, menstrual cycle. In *StatPearls*. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK500020/
14. Wakefield, C., Yao, L., Self, S., & Frasch, M. G. (2023). Wearable technology for health monitoring during pregnancy: An observational cross-sectional survey study. *Archives of Gynecology and Obstetrics, 308*(1), 73–78. https://doi.org/10.1007/s00404-022-06705-y
15. Wu, Y.-C., Su, E. C.-Y., Hou, J.-H., Lin, C.-J., Lin, K. B., & Chen, C.-H. (2025). Artificial intelligence and assisted reproductive technology: A comprehensive systematic review. *Taiwanese Journal of Obstetrics & Gynecology, 64*(1), 11–26. https://doi.org/10.1016/j.tjog.2024.10.001
16. Xiping, L., Xiaqiu, W., Lirong, B., Jin, P., & Hui, K.-K. (2022). Menstrual cycle characteristics as an indicator of fertility outcomes: Evidence from a prospective birth cohort study in China. *Journal of Traditional Chinese Medicine, 42*(2), 272–278. https://doi.org/10.19852/j.cnki.jtcm.2022.02.010
17. Yu, J.-L., Su, Y.-F., Zhang, C., Jin, L., Lin, X.-H., Chen, L.-T., Huang, H.-F., & Wu, Y.-T. (2022). Tracking of menstrual cycles and prediction of the fertile window via measurements of basal body temperature and heart rate as well as machine-learning algorithms. *Reproductive Biology and Endocrinology, 20*(1), 118. https://doi.org/10.1186/s12958-022-00993-4
18. Zaninovic, N., Elemento, O., & Rosenwaks, Z. (2019). Artificial intelligence: Its applications in reproductive medicine and the assisted reproductive technologies. *Fertility and Sterility, 112*(1), 28–30. https://doi.org/10.1016/j.fertnstert.2019.05.019
19. Zhu, T. Y., Rothenbühler, M., Hamvas, G., Hofmann, A., Welter, J., Kahr, M., Kimmich, N., Shilaih, M., & Leeners, B. (2021). The accuracy of wrist skin temperature in detecting ovulation compared to basal body temperature: Prospective comparative diagnostic accuracy study. *Journal of Medical Internet Research, 23*(6), e20710. https://doi.org/10.2196/20710
20. Wilcox, A. J., Weinberg, C. R., & Baird, D. D. (1995). Timing of sexual intercourse in relation to ovulation: Effects on the probability of conception, survival of the pregnancy, and sex of the baby. *New England Journal of Medicine, 333*(23), 1517–1521. https://doi.org/10.1056/NEJM199512073332301
21. Maijala, M., Kinnunen, H., Koskimäki, H., Jämsä, T., & Kangas, M. (2019). Nocturnal finger skin temperature in menstrual cycle tracking: Ambulatory pilot study. *Journal of Medical Internet Research, 21*(3), e13478. https://doi.org/10.2196/13478